Design and development of soft exosuit for fall intervention

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**DESIGN AND DEVELOPMENT OF SOFT EXOSUIT
FOR FALL INTERVENTION**

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DESIGN AND DEVELOPMENT OF SOFT EXOSUIT FOR FALL INTERVENTION

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School of Mechanical and Aerospace Engineering

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Design and Development of Soft Exosuit for Fall Intervention

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Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate except as acknowledged in the Author Attribution Statement. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

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Authorship Attribution Statement

This thesis contains material from 1 paper(s) published in the following peer-reviewed journal(s) / from papers accepted at conferences in which I am listed as an author.

Chapter 1 is published as J. K. Er and W. T. Ang, "Evaluation of Single HMM as a Pre-Impact Fall Detector Based on Different Input Signals," 2018 IEEE Region Ten Symposium (Tensymp), Sydney, Australia, 2018, pp. 207-212.

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The contributions of the co-authors are as follows:

- Assoc. Prof. Wei Tech Ang provided the initial project direction and edited the manuscript draft.
- I designed, implemented the system, analyzed the result, and wrote the manuscript.

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Abstract

The risk of falls along with the severity of its associated injuries increases with age. These injuries have caused significant economic loss for the whole family and their caregivers. Hence, many solutions are being developed to minimise fall risk and reduce fall injuries. There are many methods of reducing fall risks and they can be classified under four categories: fall prevention, fall mitigation, fall recovery and fall intervention. Here, a novel exosuit that is capable of assisting in recovery actions is proposed under the category of fall intervention. Although trip is the most prevalent fall type, previous studies on fall intervention have instead placed emphasis focused on slips and lateral balance.

The proposed exosuit will assist in providing a portion of the lumbar extension torque when a trip is detected while remaining transparent during Activities of Daily Living (ADLs). It is hypothesised that the assistive force provided by the exosuit will be sufficient to improve the stability of its user during a trip, as evaluated by balance indicators. The successful realisation of the exosuit depends on many components. These include a fall detection system, a base-suit for force transmission as well as a high bandwidth, high force and high stroke actuator.

The developed fall detection system involves three Inertial Measurement Units (IMUs) mounted on the torso and thighs. Each IMU outputs a set of accelerometer and gyroscope data. These data were then passed into a single Hidden Markov Model (HMM) that has been trained using Activities of Daily Living (ADLs). Validation of the system reveals a sensitivity of 90.4%, precision of 87.4%, and an average detection latency of 128.21ms. This system has shown capabilities of performing in real time from a single board computer.

The base-suit of the exosuit is responsible for providing anchor points and improving the transmission efficiency of the actuator. Two commercially available safety harnesses were used to construct the exosuit. Characterisation of the base-suit involved decoupling the force and extension measurement, as input forces will induce unwanted subject movement during measurement, which in turn changes the extension values. A simple feed-forward neural network was used to estimate the force given any extension input, along with the body parameters of the subjects. Results showed that the network was successful in predicting the force output with an average residual of 7.556N.

The last component of the exosuit is an actuator that activates only when a fall

is detected. Since a fall initiates and ends in about $500ms$, the designed actuator must have a high bandwidth. The low body stiffness and small moment arm also require the actuator to have both high force and high stroke. During walking, the body deviates in all directions and thus, the actuator must also be highly transparent to preserve normal gait pattern. The above requirements and constraints lead to the development of an actuator that is powered by constant force springs. These springs provided an instantaneous high force output while maintaining its force magnitude throughout the fall recovery period. A novel two-stage design also doubled the stroke while retaining most of the force to perform actual torso extension. This large stroke was made possible by mounting one spring in the first stage to eliminate the majority of the body's compliance. Conversely, the second stage acted on the stiffer body to perform the joint movement. The cam cleats in the actuator ensure that the user only feels the actuator force when activated. This actuator was tested to output a maximum of $183.9N$ of force within $91.67ms$ during no-load tests.

Finally, the integrated exosuit was evaluated on 15 healthy subjects for its effectiveness in balance recovery assistance with the extrapolated centre of mass (XCoM). Falls were induced using a fall inducing movable platform (FIMP) which allows transparent overground walking while allowing investigators to randomly induce a repeatable trip with ease. The experimental results proved that the exosuit provided sufficient force at the lumbosacral joint to significantly assist in the balance recovery of its user ($p < 0.001$).

Although all components of the exosuit and its integrated performance were evaluated on young, healthy subjects, the efficacy of this proposed exosuit as an assistive fall intervention device remains. The results of this thesis have revealed promising potential for the translation of this technology to the targeted elderly population. However, more work is required to factor in the slower response time and weaker muscular strength of the elderly.

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Abbreviations

ADL Activities of Daily Living. 20, 4, 5, 16, 28, 29, 30, 31, 32, 33, 39, 42, 50, 51, 59, 60, 67, 69, 72, 78, 79, 84, 85, 171, 172, 192, 196, 203

AngMom Angular Momentum. 12, 13, 15, 18, 19, 20, 29, 48, 49, 50, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 84, 114, 179, 201, 202

ANOVA Analysis of Variance. 26, 27, 34, 35, 36, 37, 158, 160, 162, 163, 165, 168, 255, 256, 257, 258, 259, 260, 261, 262, 263, 264, 265, 266, 267, 268, 269, 271, 272, 273, 274, 275, 276, 277, 278, 279, 280, 281, 282, 283, 284, 285

AUC Area Under Curve. 30, 70, 71, 79, 201, 203, 204

BBS Berg Balance Scale. 9, 195

BIC Bayesian information criterion. 53, 54

BMI Body Mass Index. 58, 91, 105, 130, 152, 171

BoS Base of Stability. 22, 23, 2, 10, 12, 14, 15, 18, 19, 20, 21, 22, 23, 24, 43, 111, 112, 113, 116, 117, 118, 161, 167, 175, 191

CFS Constant Force Spring. 23, 28, 119, 120, 121, 122, 123, 125, 177, 179

CHMM Continuous Hidden Markov Models. 31, 32, 54, 77, 85

CoD Coefficient of Determination. 94, 95, 97, 98, 105

CoG Center of Gravity. 20, 21, 23

CoM Center of Mass. 12, 13, 17, 18, 19, 22, 23, 29, 2, 5, 8, 10, 15, 18, 20, 21, 23, 24, 26, 48, 49, 50, 58, 66, 67, 68, 70, 71, 72, 111, 114, 115, 116, 117, 118, 149, 150, 178, 179, 184, 191, 194, 201

CoP Center of Pressure. 8, 22, 23, 24, 178, 179

CP Capture Point. 17, 23, 24, 25

CS Coordinate System. 63, 64

CTSIB-M Modified Clinical Test of Sensory Interaction in Balance. 171

CV Coefficient of Variation. 155

DA Discriminant Analysis. 30

DoF Degrees of Freedom. 18, 41, 43

EMG Electromyography. 32, 40

FIMP Fall Inducing Movable Platform. 14, 16, 23, 25, 29, 4, 6, 60, 123, 124, 125, 127, 128, 144, 146, 147, 148, 149, 150, 151, 153, 154, 155, 158, 163, 167, 169, 170, 171, 173, 175, 176, 177, 187, 188, 189, 191, 192, 193, 245, 255, 271

FN False Negative. 69

FP False Positive. 69

FPGA Field Programmable Gate Arrays. 195, 196

FPR False Positive Ratio. 29, 30, 201, 202, 204

GMM Gaussian Mixture Model. 47, 51, 53, 54, 55

GNA Gauss-Newton Algorithm. 135, 136

GRF Ground Reaction Force. 22, 21, 114, 115

HMM Hidden Markov Models. 13, 15, 20, 30, 31, 32, 39, 47, 31, 32, 45, 48, 50, 51, 52, 55, 56, 57, 60, 77, 78, 79, 83, 84, 85, 192, 203, 204, 205, 206, 207, 208, 209, 210, 211, 212, 213, 214, 215, 216, 217, 218, 219, 220, 221, 222, 223

ICA Independent Component Analysis. 29, 31

IMU Inertial Measurement Unit. 12, 13, 18, 19, 23, 24, 2, 4, 15, 27, 28, 29, 44, 45, 47, 57, 58, 60, 61, 62, 63, 64, 65, 67, 68, 77, 78, 79, 84, 118, 128, 129, 130, 131, 132, 139, 171, 172, 174, 176, 192, 195

IRB Institutional Review Board. 58, 171

LCC Likelihood Correlation Criterion. 53

LDA Linear Discriminant Analysis. 30

LIPM Linear Inverted Pendulum Model. 17, 23, 24

LMA Levenberg Marquardt Algorithm. 24, 25, 134, 135, 136, 137, 138, 139, 140, 141, 143

NN Neural Network. 30, 31, 99, 104, 108

NTU Nanyang Technological University. 58, 60, 79, 83, 151

PAM Pneumatic Artificial Muscle. 34, 35, 38, 40, 41

PCA Principal Component Analysis. 29

PD Proportional Derivative. 144, 145

PDF Probability Density Function. 51, 52, 54, 55

PneuNets Pneumatic Networks. 18, 35, 39, 40

PR Precision-Recall. 15, 19, 20, 30, 31, 32, 69, 70, 71, 75, 76, 79, 80, 203, 205, 206, 207, 208, 209, 210, 211, 212, 213, 214, 215, 216, 217, 218, 219, 220, 221, 222, 223

QDA Quadratic Discriminant Analysis. 30

ROC Receiver Operating Characteristics. 15, 29, 30, 69, 201, 202, 203, 204

SBC Single Board Computer. 18, 60, 61, 79, 192, 195

SCI Spinal Cord Injury. 8

SMEM Split and Merge Expectation Maximization. 51, 53, 55

SPA Soft Pneumatic Actuators. 35

SPM Statistical Parametric Mapping. 16, 26, 27, 29, 33, 34, 35, 36, 37, 154, 155, 156, 157, 158, 159, 160, 162, 165, 168, 180, 182, 183, 245, 246, 247, 248, 249, 250, 251, 252, 253, 255, 256, 257, 258, 259, 260, 261, 262, 263, 264, 265, 266, 267, 268, 269, 271, 272, 273, 274, 275, 276, 277, 278, 279, 280, 281, 282, 283, 284, 285

StD Standard Deviation. 178, 182, 184, 185

SVM Support Vector Machine. 29, 30, 32

SZU Shenzhen University. 58, 59, 60, 171

TN True Negative. 69

TP True Positive. 69

TPR True Positive Ratio. 19, 20, 29, 30, 71, 75, 76, 77, 80, 201, 202, 204

USB Universal Serial Bus. 18, 60, 61, 172

VMS Velocity Matched Scaling. 24, 25, 50, 133, 134, 138, 139, 140, 141, 143

XCoM Extrapolated Centre of Mass. 40, 50, 3, 18, 19, 25, 48, 179, 183, 184, 185, 186, 187, 188, 194

ZMP Zero Moment Point. 40, 21, 22, 23, 25, 179, 181, 182, 183, 184, 185, 186, 187, 188

Symbols

h_0 initial height. 17, 23, 24

f_s frequency of sine waves. 50, 134, 135, 137

ϕ phase angle of sine wave. 50, 134, 135, 137

x_{com} CoM along the x-axis. 20, 22, 24

M total mass of the body. 20, 21, 22, 23, 24

m^i mass of an individual body. 20, 21, 22, 49

$p_{x,com}^i$ position of i^{th} body CoM in the x-axis. 20, 21, 22

n number of individual bodies. 20

$M_{zmp,y}$ sum of moments about the y-axis. 21

$\mathbf{p}$ positional vector in x, y and z-axes. 21, 22, 23

$\mathbf{F}_{x,z}$ vector forces on the x and z-axes. 21

p_x position along the x-axis. 21, 23, 24

F_z force acting along the z-axis. 21

p_z position along the z-axis. 21

F_x force acting along the x-axis. 21, 23, 24

g gravitational constant at $-9.8ms^{-2}$. 21, 22, 23, 24

$\ddot{p}_{z,com}^i$ acceleration of i^{th} body CoM in the z-axis. 21, 22

$p_{z,com}^i$ position of i^{th} body CoM in the z-axis. 21, 22

$\ddot{p}_{x,com}^i$ acceleration of i^{th} body CoM in the x-axis. 21, 22

x_{zmp} ZMP along the x-axis. 21, 22, 181

$p_{z,com}^{\ddot{}}$ acceleration of whole body CoM in the z-axis. 21, 22

z_{zmp} ZMP along the z-axis. 21, 181

$p_{x,com}^{\ddot{}}$ acceleration of whole body CoM in the x-axis. 21, 22

z_{com} CoM along the z-axis. 22

y_{zmp} ZMP along the y-axis. 22

y_{com} CoM along the y-axis. 22

$p_{y,com}^{\ddot{}}$ acceleration of whole body CoM in the y-axis. 22

$F(\mathbf{p})$ localised pressure/force on a point indicated by $\mathbf{r}$. 22, 23

x_{CP} Capture Point along the x-axis. 24

v scalar velocity. 24

$\mathbf{H}$ angular Momentum the CoM. 49

$\mathbf{p}^i$ positional vector in x, y and z-axes for individual body. 49

$\dot{\mathbf{p}}^i$ velocity vector in x, y and z-axes for individual body. 49

I^i global rotational inertia tensor of the i^{th} body. 49

ω^i angular velocity vector of the i^{th} body. 49

R^i rotational matrix of the i^{th} body referenced to the global coordinate system. 49

I_{local}^i local rotational inertia tensor of the i^{th} body. 49

$\mathbf{H}_{ank}$ angular Momentum about the ankle. 49

$\mathbf{p}_{ank}^i$ positional vector for individual body, referenced from the ankle. 49

$\dot{\mathbf{p}}_{ank}^i$ velocity vector for individual body, referenced from the ankle. 49

$L(\theta_j|X_n)$ likelihood function with X data points and θ parameters. 52, 53

θ_j mixture parameters such as means (μ_j) and covariance (Σ_j). 52

$\mathbf{X}_n$ n multi-dimensional data points. 52
 π_j prior of the j^{th} mixture. 52, 53, 55, 56
 Σ_j covariance of the j^{th} mixture. 52, 53
 μ sample mean. 52, 53, 57
 μ_j mean of the j^{th} mixture. 52
 $E_{div,j}$ modified local kullback divergence for splitting 2 Gaussian Mixture Model (GMM) mixtures. 52, 53
 $D_{LKD,j}$ local kullback divergence. 52
 $CV_{max,j}$ maximum coefficient of variation of all axis. 52, 53
 E_{corr} modified correlation criteria for merging 2 GMM mixtures. 53
 U_{corr} original correlation criteria. 53
 A state transition probability matrix of every HMM state. 54, 55
 B emission matrix of every HMM. 54, 55, 56
 π prior of every state or distribution. 54, 55, 57
 N_s number of hidden states. 54, 57
 N_m number of GMM mixtures. 54
 a_{ij} probability of going from state i to state j . 54, 55, 56, 57
 b_{j,O_t} probability of the observation O_t belonging to state j . 54, 55, 57
 t timepoint. 55, 56, 57, 134
 α forward probability of an observation sequence. 55, 56, 57
 O_t observation at timepoint t . 55, 56
 s_j j^{th} state for a HMM. 55, 56, 57
 λ model parameters of each HMM. It includes A, B, π, N, M . 55, 56, 57
 c_{im} weight of the i^{th} state for the m^{th} probability density function. 55, 56

$N(O_t|\mu_m, \sigma_m)$ probability density of a Normal distribution for an observation, given the mean and standard deviation. 55

β backward probability of an observation sequence. 55, 56

ζ state transition probability. 56

γ state probability. 56, 57

Σ_{cov} covariance. 57

Q^i rotational quaternion of the i^{th} body referenced from the initial pose. 62, 64, 131

Q_{init}^i rotational quaternion of the i^{th} body at the initial pose refereced from the global coordinate system. 62, 131

Q_{raw}^i rotational quaternion of the i^{th} body obtained directly from the IMU without any processing. 62, 131

ψ heading angle. 63

q_x x component of a quaternion. 63

q_z z component of a quaternion. 63

q_w w component of a quaternion. 63

q_y y component of a quaternion. 63

Q_ψ inverse heading rotational quaternion. 63, 64, 131

Q_{ro}^i rotational quaternion of the i^{th} body reoriented into the sagittal plane. 64, 65, 131

Q_{acc}^i acceleration vector expressed as a quaternion of the i^{th} body reoriented into the sagittal plane. 64

Q_{rawacc}^i raw acceleration vector expressed as a quaternion of the i^{th} body. 64

v_t tangential velocity scalar. 64

ω angular velocity scalar. 64

r_{limb} length of the specified limb. 64, 65, 66

Q_{dir} direction vector expressed as a quaternion. 65

$Q_{\hat{y}}$ length of the specified limb. 65

$\mathbf{p}_{dir}$ direction vector. 65

$\mathbf{p}_{dir,yz}$ direction vector projected onto the y-z plane. 65, 66

$p_{dir,y}$ y component of the direction vector. 65

$p_{dir,z}$ z component of the direction vector. 65

$\dot{\mathbf{p}}$ velocity vector in the global coordinate system. 66

ω_x angular velocity about the x-axis. 66

$\mathbf{p}_{dir,xz}$ direction vector projected onto the x-z plane. 66

ω_y angular velocity about the y-axis. 66

$\mathbf{p}_{dir,xy}$ direction vector projected onto the x-y plane. 66

ω_z angular velocity about the z-axis. 66

σ_s stress. 91

E Young's modulus. 91

ϵ strain. 91

F_{act} force created by actuator. 92

F_{torso} force created by torso's muscle. 92

$\Delta L_{base-suit}$ combined deformation of the base-suit, actuator and subject's body. 92, 94

K stiffness ratio. 92, 94

y_i model output. 99, 135

m_t first moment vector (mean) for *Adam* solver. 100

ξ exponential decay rate. 100

m_{t2} second moment vector (uncentered variance) for *Adam* solver. 100

Φ gait phase angle. 132, 133, 136, 138, 139

θ_{torso} torso flexion angle. 132, 133

κ scaling factor for VMS. 133, 134, 141

$F_s(t)$ magnitude of sine wave at timepoint t. 134

A_s magnitude of sine waves. 134

B_s offset of sine waves. 134, 135

Λ vector of parameters for the sine wave (f_s, ϕ) . 135, 136

$\mathbf{X}$ vector of model inputs. 135, 136

x_i model inputs. 135

$\mathbf{Y}$ vector of model outputs. 135, 136

σ_Δ Jacobian matrix. 135, 136

J Jacobian matrix. 135, 136

γ_δ step size for optimization methods. 136

λ_δ damping factor for optimization methods. 136

x_{xcom} XCoM along the x-axis. 184

z_{xcom} XCoM along the z-axis. 184

Chapter 1

Introduction

1.1 Background

Most developed countries face the problem of increasing fall risks with their ageing population. Ageing increases risks of exposure to neurological insults (e.g. head injury, stroke, spinal cord injury, Parkinson's Disease, peripheral neuropathies, etc.), musculoskeletal problems (e.g. chronic ankle sprains, chronic degenerative low back pain, scoliosis, amputation, etc.) and vestibular deficits (e.g. benign paroxysmal positional vertigo). These issues weaken balance control and eventually, lead to falls. Generally, healthy adults aged 65 and above will fall at a mean rate of 0.65 times annually, and this rate doubles for adults above 75 years old [1].

Fall is defined as *"an unexpected event in which a person comes to rest on the ground, floor or lower level"* [2]. Therefore, a fall is initiated when instability occurs and ends with an impact at a lower level. A fall impact can be avoided when the person is able to perform balance recovery. Here, the fall has occurred but has prematurely ended. Confusion often arises when other nouns are combined with fall, such as fall prevention, fall mitigation, fall recovery and fall intervention. These terminologies will be used throughout this thesis. Hence, to enhance clarity, the definitions for these terminologies have been standardised and defined as follow:

Fall Prevention: A device or action that prevent instability from occurring. Thus, no fall occurs.

Fall Mitigation: An act of reducing the fall impact. For example, putting a mattress to cushion the fall impact.

Fall Recovery: An act of recovery after the fall impact has occurred.

Fall Intervention: An action taken during the fall to prevent or reduce the severity of the fall impact. Self-balance recovery after the moment of instability is defined as self intervention.

Fall prevention is the most common method currently used. A typical method involves the installation of support railings and non-slip mats around the environment of the elderly. However, this solution is not viable at all locations due to high costs and inconvenience. With insufficient installations of fall prevention facilities, the elderly become less confident of manoeuvring in such environments. Hence, a vicious cycle is generated - the elderly are less likely to exercise due to high risks of falling, leading to increase rate of muscle degradation which decreases body stability and consequently, further increasing fall risks. An alternative fall prevention solution is to rely on walkers or crutches to widen the elderly's base of support. Nonetheless, this method is only suitable for the elderly with sufficient arm and core strength. Unfortunately, the elderly faced higher risks of falling have muscle degeneration issues. Thus, they are unsuitable to use walkers for a prolonged period. Robotic solutions provide another form of fall prevention, such as KineAssist[3], Andago[4], SoloWalk[5] and NaTure-gaits[6]. They provide body weight support via the underarms or overhanging harness, which eliminates their chances of fall. A robotic exoskeleton, with extended balance stabilisers on the lateral sides, was also created to increase the base of stability [7]. However, it lacks control in body weight positioning during walking. The Rex exoskeleton [8] provides another innovative and unique way for fall prevention. Users sit in the "*driver's seat*" of Rex and control its movement using a joystick. Rex handles the balance of both the machine and the user by travelling exceptionally slowly and walking in a highly unnatural manner to always constraint the CoM within the BoS. The CoM of a healthy gait will exceed the BoS most of the time. However, these robotic solutions are often slow, bulky, heavy and overly cautious in their balance control as their goal is to eliminate any chance of falling.

Fall mitigation explores solutions for reducing fall impact severity. The most common example is an airbag that inflates during a fall-onset to cushion the impact of fall [9–11]. These solutions commonly rely on IMU to detect the onset of fall, which then triggers the inflation of an airbag mounted on the hip. Subjects have to fall on top of the airbag for fall mitigation. However, these airbags are often under-pressured and/or not fully enclosing the impact area due to their focus on portability. Injuries still occur due to the lack of sufficient cushioning. Other fall mitigations strategies such as impact absorbing flooring have been successful in

reducing fall injuries, but the likelihood of falling was higher on the softer flooring [12].

Fall intervention describes solutions that detect the onset of fall and prevent the fall impact from happening. These solutions attempt to provide the required freedom of movement that fall prevention solutions cannot, while eliminating the fall impact that is still present in fall mitigation solutions. Due to the high requirements for limbs synchronisation, actuation speed and fall detection accuracy, the number of attempts at fall intervention is few and far between. To the best of the authors' knowledge, there are only two attempts at robotic fall intervention solutions. The first attempt was a pelvis exoskeleton developed by the BioRobotics Institute of Scuola Superiore Sant'Anna [13]. This pelvis exoskeleton stiffens the hip joint when a slip is discovered and hence, reducing the widening of the stance legs. The results are promising as this system can reduce the XCoM during a detected slip. However, the slip is conducted on a treadmill which does not mimic the actual body dynamics during walking. The second attempt was with the MindWalker exoskeleton [14] that assists in reducing frontal planes hip deviations using powered hip abduction/adduction. XCoM was used to detect deviations from normal walking, and this system compensates with adjusted step width. Notably, trip, which is a more common fall type [15], has not been studied in both cases. Trip is approximately 7 times more prevalent than slip [15, 16].

Here, a fall intervention device that enhances mobility balance is proposed. The proposed solution is targeted at the elderly population and uses a soft exosuit for fall intervention. Soft exosuit uses soft materials and actuators to provide joint actuation which eliminates the joint misalignment and heavy weight of the conventional rigid exoskeleton. Despite the need for extensive modelling and feedback to accurately execute position control, the soft exosuit offers excellent force control capability while remaining lightweight. The weight of the system not only introduce better system transparency and control but also reduces the chances of injuries should the system fails, or the user falls. We hypothesise that the proposed soft exosuit can serve as a fall intervention device that assists in restoring stability after a fall-onset. In addition, this proposed system will only activate upon detection of a fall.

The proposed exosuit is divided into multiple components (Figure 1.1). Firstly, the exosuit fall intervening system must start with a real-time fall detection system. This fall detection system is required to detect falls before the impact, i.e. pre-impact fall detection. The faster the pre-impact fall can be detected, the earlier the system can intervene and provide sufficient assistive recovery. Next, an actuator

is required to provide high force with high bandwidth to help the user recover in time. An accompanying base-suit is also necessary to direct forces from actuators to induce joint movements with maximum efficiency. Poor transmission efficiency will require larger actuators to compensate, which reduces usability. Lastly, the fall detection system, actuator and base-suit are combined and synchronised to obtain assisted balance recovery system. Additionally, a FIMP is created to produce repeatable and reliable falls for exosuit prototyping and validation. FIMP requires gait phase detection algorithm and fall inducing mechanisms to trigger different falls, which then induce different recovery motion. These different fall scenarios and recovery motion are used to validate exosuit usability under multiple scenarios.

Figure 1.1: Exosuit components. The arrows represent the flow of information between different components

1.2 Objectives

The main objective is to develop an assistive soft exosuit to provide in-time balance recovery assistance during falls. It can be further separated into five specific aims:

1. Implement a pre-impact fall identification system from IMUs data to accurately discern ADLs from falls
2. Design a high force, stroke and bandwidth actuator to deliver sufficient assistive forces for balance recovery
3. Design and characterise an adjustable base-suit made of webbings for the exosuit to direct forces effectively from actuator to body
4. Implement a gait phase identification system from IMU data to induce the desired fall recovery motion
5. Create real-time fall inducing movable platform to produce the necessary fall dynamics while remaining transparent otherwise
6. Evaluate the effectiveness of the exosuit during near-fall scenarios

1.3 Scope

- The targeted population of this exosuit are the elderly who are mobile without external help but are at moderate risk of falling (Berg Balance Scale score between 40 to 21 [17]). Herein, the exosuit is designed to support only a fraction of the user's force in order to achieve wearability. Hence, subjects that are not self-mobile (e.g. spinal cord injury and stroke patients) require more force than what this exosuit can provide.
- As the most common fall type, only trip is targeted in this fall intervention solution [15]. Although slip is the second most common fall type, when compared to a trip, slip is difficult to intervene. During a slip, the stance leg will slide forward. However, it is undeterminable whether the forward stance leg or both legs will slide forward at the instance of a slip. Under the scenario of double leg slip, the body's CoM will be posterior to the base of stability. This causes immense difficulty in designing any actuator sequence that can assist hip flexion without any external support. An attempt to assist hip flexion may instead reduce the pressure between the foot and ground, which further decreases friction, leading to more severe slip. On the other hand, during a trip, there will be a leg on the ground with proper friction, alleviating the problem mentioned above. The slip intervention solution [13] that was studied by BioRobotics Institute of Scuola Superiore Sant'Anna occurred on a high friction treadmill that does not replicate true slip conditions.
- The pre-impact fall detection is limited to only differentiate falls from the ADLs that do not have external support (e.g. walking, standing and reaching without a walker). This is because ADLs with external support (e.g. sitting, walking with a walker) has an extended base of stability that is not measurable with the tools limited by the scope of a wearable exosuit.
- The actuator is targeted to satisfy the force, stroke and bandwidth of the lumbosacral joint assistive torque. The lumbosacral joint has been identified to be the most significant factor in user stability (see Chapter ch:actuator).

1.4 Organization

This thesis consists of 8 chapters, including this introduction. The organisation of the rest of the thesis is as follows:

Chapter 2 describes the dynamics and demographics of fall, reviews various actuators, sensors and algorithms and identifies different research gaps.

Chapter 3 focuses on the motion sensing platform and two methods of fall detection namely angular momentum and hidden Markov Model.

Chapter 4 explains the selection of materials and considerations for the exosuit. Stiffness of the whole system is also studied and modelled.

Chapter 5 describes the creation of a high force, high stroke and high bandwidth actuator; along with their strengths and limitations.

Chapter 6 proposes a method of extracting gait phases and uses it to create a fall inducing movable platform FIMP.

Chapter 7 combines components from all previous chapters to form a functional exosuit. The completed exosuit as a balance recovery assistive system is evaluated and discussed.

Finally, the thesis is concluded in **Chapter 8**.

Chapter 2

Literature Review

This literature review is organised to first discuss the potential impact of this research's target audience - elderly with moderate fall risk. Next, the major types of falls accompanying old age will be presented. Subsequently, different fall solutions are then evaluated with emphasis on why fall intervention solution should be the way forward. Then, different balance models that represent human stability will be presented with their respective strengths and weaknesses. Following the balance indicators, a detailed review was conducted on fall detection algorithms, with an explanation given on why balance indicators cannot be implemented as fall detection algorithms.

Due to the usage of soft robotics, and inclusion of a fall inducing platform for exosuit validation, this literature review will also cover the state of the art for soft actuators/sensors, fall inducing methods and gait detection algorithms.

2.1 User Demographics

The population that is most likely to benefit from this research would be the elderly and paralysed patients.

Ageing is an inevitable process that brings about many problems, such as loss of muscle and bone mass [18], degradation of joints [19] and slower response time [20]. These problems lead to a higher risk of falling, which might eventually cause them to be wheelchair bound, leading to more problems like weaker immune and regulatory system [18, 21–23]. Between now and 2030, Singapore will witness an unprecedented age shift. Based on Committee of Ageing Issues [24], the number of residents aged 65 years or older will multiply threefold; from 300,000 in 2005 to 900,000 in 2030. The 2014 population report by Singstat [25] reported that the ageing

population in Singapore has reached 440,000. By 2030, 1 out of every 5 residents will be a senior citizen. This problem is not exclusive to Singapore. Many developed countries, such as the US, Japan and Korea face similar population woes.

This research could also be targeted at an alternative audience - paralysed patients with disabilities. Paralysis is the loss of control over a part of the body. Two of the most common causes of paralysis are stroke and Spinal Cord Injury (SCI) [26]. There are 9 million stroke cases yearly, and as of 2011, there are 30.7 million stroke survivors [27]. In Singapore, stroke amounts to the third highest overall disease burden among other diseases [28] and 73% of these patients lose their walking ability within the first week [29]. On the other hand, there are 250,000 to 500,000 new SCI patients in the world each year [30], with an estimated 14 million survivors as of 2010 [31]. Most of them also lose their walking ability as a result of a partial loss of both sensory and motor control of their lower limbs [32].

Although fall intervention is crucial to both groups of individuals, the elderly will be the focus of this project. In particular, the elderly with medium fall risk would be the target. Most of the elderly are slower and weaker than the healthy population. Unlike paralysed patients, they are not immobile with multiple complications. Given this scope, healthy and young subjects can first be recruited for faster and safer prototyping while retaining relevance to the elderly.

2.1.1 Elderly Fall Risk

An individual's balance keeping-ability peaks at the age of 20 to 21 years old, and then starts decreasing with age [33]. Muscle strength necessary to achieve balance decreases at about 3.6% in men and 2.8% in women per year [34]. Decreased muscle quality, instead of muscle atrophy was found to be the major contributing factor to the loss of muscle strength [34]. This decline in muscle strength caused instability in the upper body during walking [18, 35] and a reduction in the ability to detect and process proprioceptive and sensory information [36].

As muscle abilities decline, the elderly began to assume a shorter step length, with a longer step duration to reduce their upper body acceleration. However, this has led to lower gait stability, especially in the mediolateral direction [18, 37]. An excessive lateral momentum was also found in such balance-impaired gait [38], with increased CoM and Center of Pressure (CoP) inclination angle in the coronal plane [39].

Cognitive impairment can also cause of gait instability. However, its significance

and implications have been inconclusive. The cognitive ability of elderly was first identified to affect the geriatric rehabilitation course and functional ability of the patient. However, the study has failed to predict the walking and stair climbing ability [40]. On the other hand, when the elderly with normal mental capacity were asked to walk and perform other tasks simultaneously, their gait pattern changed [41]. This indicated that cognitive capability has a role in affecting walking ability. Gait instability has also been found to be associated with silent infarcts (detectable in 7.2 - 28% of the general population), cerebral microbleedings (occurring in 4.7 - 23.5% of the general population) and cerebral white matter microlesions (present in 90% of people aged 60 years and above) [42].

The ultimate consequence of weak balance control is fall. On average, healthy individuals aged 65 and above fall 0.65 times per year and this rate doubles among people older than 75 years old [1, 43]. In the contemporary rehabilitation care paradigm [18, 21–23], patients' mobility and independence are encouraged and ironically, the risks of falls might inadvertently increase [18–22, 24].

Berg Balance Scale (BBS) is a 14-item scaled checklist that has often been used to measure the balance status and predict fall risk of elderly in a clinical setting with success [44–47]. Hence, the elderly with a BBS score between 21 to 40 is the targeted audience of the proposed fall intervention solution. These individuals have been identified as having a medium fall risk under the BBS interpretation.

2.2 Fall dynamics

The dynamics of falls are vastly different depending on the direction and cause of fall. Hence, falls are often separated into forward fall, backward fall and lateral fall for easier classification [16]. However, the causes of falls are commonly unobserved or obscured. True falls are relatively rare and occur everywhere and thus, proper documentation of true falls is a near impossible task. Fortunately, a three-year observational study of elderly in 2 long term elder care facilities have successfully video-captured data of how the elderly within these facilities fall (Table 2.1).

Interestingly, the most common type of fall is due to incorrect weight shifting - an internal factor that is difficult to control and reduce its risks. However, an exosuit with built-in sensors and actuators could allow continuous monitoring of the subjects and provide near-instant recovery assistance when necessary.

Among the various external fall factors (trip, external push/pull and slip), trip is the most prevalent – accounting for up to 21% of all instances of fall. A trip

Table 2.1: Data collected from a 3 year observational study in 2 long term elder care facilities in British Columbia, Canada using digital video cameras [15].

Fall type	Number of fall	Percentage of fall
Incorrect transfer or shift of bodyweight	93	41%
Trip or stumble	48	21%
External push/pull	25	11%
Loss of support with external object	25	11%
Collapse or loss of consciousness	24	11%
Slip	6	3%
Could not tell	6	3%

is typically caused when the swing foot is obstructed by an unexpected external barrier. This causes a sudden arrest of the perturbed foot which is accompanied by a surge of unwanted dynamical forces and momentum due to the unpredicted BoS. Frontal falls are often caused by trips [16]. On the contrary, slip is often caused by the terminal swing leg having contacted a slippery or moving surface, as it is transitioning to stance. The sudden acceleration of the slipping leg causes the body's CoM to waver in all directions as sufficient friction force is not achieved on the slipping leg. Hence, slip causes fall in a variety of directions, which makes it difficult to predict and assist.

2.2.1 Recovery Strategies

A typical fall starts and ends with an impact in about 500ms [20], while significant muscle activities occur within a short span of 90ms to stiffen the joints for another 100ms before other muscles intervene and synchronise to obtain desired output motion [48]. Different fall types require different recovery strategies. The Elevating and Lowering strategy are strategies for aiding the recovery of forward falls [49] (see Figure 2.1).

The Elevating strategy is adopted when an external disturbance occurs at the early to mid swing gait phase. During a trip in the mid to late swing phase, the Lowering strategy is engaged instead. The Lowering strategy requires an additional step to clear the obstacle or stabilise from the disturbance. The determining factor of forward balance recovery is the ability to widen the BoS [51] and to arrest the trunk dynamics after touchdown [20]. A lesser known trip recovery strategy is the skipping strategy [52]. When the perturbed leg cannot clear the obstacle during the early to mid swing phase, the contralateral leg will skip forward to regain stability.

Figure 2.1: Recovery Strategies for forward fall. Image from Shiratori et. al [50]

Backward falls are usually caused by a slip, and its recovery strategy varies significantly according to the prior knowledge of the ground friction [53]. For the first slip recovery response, the slipped foot will immediately attempt to adopt a flat-footed configuration to the ground. Simultaneously, the contralateral leg will try to touchdown as fast as possible and push the centre of mass forward. These responses require extension and flexion of the perturbed and unperturbed leg respectively. Subsequent walking gait on the slippery floor will involve the implementation of the Surfing strategy where the the swing foot slides forward rather than attempting to step off quickly. Surfing strategy is adopted to increase the contact area between the foot and the ground [53]. The critical factor that determines the risk of slip and fall is the displacement of the slipping foot.

Lateral balance recovery involves either side or crossover stepping strategy, with the side step being more common [54, 55]. Walking aids commonly used by the elderly has shown to impede the ability of its users to perform lateral balance recovery [56].

The focus of this project is aimed at recovering from trips that cause frontal falls as they account for more than 21% of all kinds of falls among the elderly [15]. Furthermore, the recovery strategy of frontal falls does not differ significantly from regular walking. These recovery strategies include the elevating and lowering strategies [49, 57], which both can be described as an elaborate walking pattern with more powerful force exertion, while maintaining the same muscle coordination as regular

walking.

2.3 Existing Fall Solutions

As mentioned in Chapter 1, there are several commonly used terms to describe fall solutions. Here, they are clearly defined, and examples for each type of solutions are discussed.

Fall Prevention: A device or action that prevent instability from occurring. Thus, no fall occurs.

Fall Mitigation: An act of reducing the fall impact. For example, putting a mattress to cushion the fall impact.

Fall Recovery: An act of recovery after the fall impact has occurred.

Fall Intervention: An action taken during the fall to prevent or reduce the severity of the fall impact. Self-balance recovery after the moment of instability is defined as self intervention.

Each of the fall solutions will be evaluated in the following sections.

2.3.1 Fall Prevention Solutions

All solutions that increase the base of stability of the users, or constraint the users within their BoS, fall under the category of fall prevention. The most common fall prevention method is through environmental modifications such as railings, grab bars, slip-resistant mats around bathrooms and improved lightings [23]. Railings and grab bars increase the user's BoS. However, they are costly to install at every corner. Furthermore, in order not to cause hindrance to human traffic, both railings and grab bars require wall mounting. Slip-resistant mats can be used to prevent slips, but face the same cost considerations as the railings. Walker or other walking aids provide a mobile alternative to railings. Yet, they are only suitable for users with sufficient arm and core strength, and they are not as stable as the railings. Walkers may even hinder the recovery of fall under certain conditions [56].

A wheelchair may eliminate most of the fall risks, but it brings about inconvenience as it can only travel on flat ground while requiring a large footprint. Besides, long-term patients who use wheelchairs suffer from poor renal function, spasticity,

hypotension, depression [22] and even reduced respiratory and circulatory system functionalities [21].

Robotics technology can also provide fall prevention solutions, and they are categorised into the following:

1. Standing Wheelchair
2. Mobile Platform
3. Bipedal Exoskeleton

Standing wheelchair

Standing wheelchair provides the same stability advantages as regular wheelchair while reducing the health and psychological problems associated with it. Standing wheelchair further provides a sense of independence to the user as they can now perform chores like a regular human being. Standing wheelchairs can be further classified into those that require users to lean behind (Figure 2.2) or lean forward (Figure 2.3). Each configuration has its advantages, but the majority of conventional standing wheelchairs are back leaning. There are more back leaning configurations as it is easier to configure a normal wheelchair to the standing position. However, users using back leaning standing wheelchair may be unstable when leaning too far forward. This lean forward posture is mostly adopted when doing typical household chores. Examples of back leaning wheelchairs are Laddroller, Shirley Ryan Ability-lab manual standing wheelchair [58], Paragolfer [59], C1000 SF Ottobock standing wheelchair [60], UpNRIDE [61], and LEVO standing wheelchair [62].

On the contrary, forward-leaning standing wheelchairs require users to lean forward, making them more versatile in day to day activities. One example is the commercially available Tek RMD [63]. However, the user must shift from a regular wheelchair to the standing wheelchair, making it a dangerous task for some patients.

Mobile Platform

These systems consist of robots that follow the patient around flat surfaces while providing body weight support through a rigid base (Figure 2.4). They allow users with even very weak lower limbs to travel upright because of the adjustable body weight support system. However, these systems have large physical footprints,

Figure 2.2: An example of a back assisted standing wheelchair (Pegasus II standing wheelchair)

Figure 2.3: An example of front assisted standing wheelchair (TEK RMD [63])

Figure 2.4: An example of a body weight support movable platform (KineAssist [3]).

Figure 2.5: An example of front assisted movable platform (SoloWalk [5])

Figure 2.6: An example of back assisted movable platform (NaTUre-gaits [6])

making them unwieldy in small homes. Nonetheless, these systems can be helpful in environments with less space constraints. Examples of such systems with overhanging body weight support are KineAssist [3], WalkTrainer [64], Andago[4] and WHERE I and II [65].

There are existing mobile platforms that attempts to reduce the footprint of the overhanging harness by assisting users from the front or back position. Examples of front assisting platforms are EXPOS [66] and SoloWalk [5] (Figure 2.5). EXPOS [66] constraints users to their BoS with a rigid arm extending from a frontal movable platform while providing additional joint torques. SoloWalk [5] provides stability via extended arms that support the users from their underarms. These platforms may have reduced the overall machine and human footprint slightly, but the subject's range of motion and reach distance will be significantly reduced.

On the contrary, back leaning allows for greater user's range of motion. An example is MRABT [67], which provides balance assistance via a 5 bar linkage, and NaTUre-gaits [6] that uses an extended armrest from a back movable platform. Although these devices are relatively smaller than the overhanging harness systems, they still require a large turning radius and a large physical footprint relative to the proposed exosuit solution.

Systems such as Lokomat [68] and LOPES [69] behaves similar to the overhanging harness movable platform, but they are rehabilitation devices constraint to a treadmill. Hence, they are excluded in this review.

Bipedal Exoskeleton

The bipedal exoskeleton has the most potential to succeed in everyday life. It has the smallest footprint out of the other fall solutions and can be brought anywhere as it has a small footprint.

A robotic exoskeleton with extended balance stabilisers on the lateral sides maintains a constant wide BoS during walking. The balance stabilisers move opposite to the user's ipsilateral leg, ensuring that the CoM is always constraint within the extended BoS. However, the stabilisers limit the shifting of CoM in the coronal plane, resulting in instability during the gait initiation process.

The REX [8] is an exoskeleton that handles all the balance of the subject by itself. It can be described as a bipedal vehicle that the user sits inside. Due to its design and requirement to ensure stability no matter what tasks the user is doing, the REX has a very unnatural gait pattern. It also has a locomotion speed of only 0.05m/s versus an average walking speed of 1.4m/s [70].

Other notable exoskeletons such as ReWalk [71], HAL [72], Indego [73], eLEGS [74], Ekso [75] and MINA [76] provide torque assistance to the user's limbs. Unfortunately, they all rely on the user's own ability to maintain their balance with walking aids while using the exoskeleton. Hence, they are not reviewed under the purpose of fall solutions as they do not provide balance assistance at all.

2.3.2 Fall Mitigation Solutions

Fall mitigation includes all solutions that reduce the severity of fall. The most notable example is the airbag which inflates during the onset of fall. These airbags rely on IMUs to detect the onset of fall which triggers the airbag inflation. The differences between fall detection algorithms are discussed in Section 2.5. Several

designs exist for the airbag placements around the user. The simplest would be two airbags that inflate from the lateral sides of the waist belt to protect the hips in the lateral directions [10, 77, 78]. They provide the most transparent experience to the user in terms of wearability. However, it has been reported that even then, the acceptability is not high. Additionally, the lateral hip airbags design does not account for falls in the other directions and also the secondary rotation induced after the impact that may injure the limbs and head. As such, airbag designs that cover the entire waist and head are safer for the user during fall [9, 11]. However, their deflated form is much larger than the waist belt design, which further decreases the acceptance rate. Moreover, other problems exist that influence the efficiency of the airbag significantly, such as the pressure of the airbag and the inflation duration. A safer design would require a large body coverage of the airbag which then requires a large amount of air that inevitably increases the weight and size of the compressed air canister that the user has to carry around continuously.

Another fall mitigation solution is the impact absorbing flooring. A 2-year study with a total of 6,641 collected falls found that the impact sustained by the elderly decreased significantly, resulting in a lower fracture rate on softer floors [79]. Another 2.5 years study with 254 recorded obtained the same conclusion using a commercially available impact absorbing flooring [12]. However, both studies have more falls per area of flooring on the softer floor versus the rigid floor. This suggests that even though a softer floor can lead to lower fall impact, it increases the risk of falling.

Fall alarm or panic button sends alerts to the caregivers of the elderly whenever a fall is detected [80, 81]. These devices are also classified under fall mitigation as they reduce the severity of fall by providing fast assistance to the injury [82]. Vigi'Fall is a commercially available system that consists of an adhesive body sensor, infrared activity sensor and a base station that processes the data and calls for help if fall is detected [80]. The adhesive body sensor is attached to the user's chest to detect their acceleration and angular velocity. The ecosystem of sensors attained a sensitivity of 62.5% and specificity of 99.5%. The requirement of an activity sensor and a base station limits the use of Vigi'fall to a specific location only. Another system relies only on an accelerometer and barometer mounted on the subject's waist [81], and they reported a sensitivity of 95.71% and a specificity of 97.78%. However, their number of test scenarios are limited, and inaccuracy may arise from comparing fall scenarios simulated by young volunteers with ADLs performed by elderly. An additional example may be the Apple Watch Series 4 with their in-

built fall detection system [83] with no reported system accuracy. Due to safety requirements, device manufacturers will often tune the system to have very high specificity, while leaving the false alarms to be remedied by the user. This reduces the acceptance of the system as most of the elderly would not want to be thought of as needy and helpless individuals.

All of the fall mitigation solutions assist or notify the caregivers only after the fall impact has occurred, which may be detrimental to the frail elderly. Hence this project chooses to focus on fall intervention solution which intervenes and stops the fall impact from occurring. Nonetheless, fall mitigation solutions are handy as a fail-safe device for fall intervention solutions.

2.3.3 Fall Recovery Solutions

Fall recovery solutions describes actions, tools and devices that aid in recovery from a fall after the fall impact has occurred. These include the solutions where user gets up from the fall independently or with assistance from their caregivers.

ResQUp [84] is a device that has multiple levels for fallers to grab and regain their seating position after a fall. It behaves like a foldable staircase that consists of multiple levels at 4 to 6 inches apart. This category of solution is not commonly investigated as users have already sustained fall injury. Hence, only one solution has been reported.

2.3.4 Fall Intervention Solutions

Fall intervention solutions operate between the boundaries of fall prevention and fall mitigation solutions. These solutions detect the onset of fall and stop the fall impact from occurring. They have the advantage of being the least obtrusive to the user as they assist only when needed. Furthermore, they aim to prevent any injury from happening as the fall impact is averted through just-in-time recovery assistance. Yet, the attempts at fall intervention solutions are lacking, as they face many constraints as listed below:

Short Operating Time Window: The duration between fall onset to fall impact is around 500 ms [20]. This time window has to be further divided to account for fall detection latency and actuator activation/operating duration.

Large Force Requirement: Considering the short operating time window, the assistive force generated by actuators have to be substantial. This is to arrest and

reduce the unwanted fall momentum before the fall impact.

Limbs Synchronization: Different fall types requires different recovery motion as described in Section 2.2.1. Incoherent assistive forces will hinder the recovery motion and even cause the fall to be more severe than what the perturbation force has induced.

Fall Detection Accuracy: Unlike fall mitigation solutions where false alarms from airbag systems or alert systems can be easily ignored, fall intervention system exerts force on the subject in an attempt to arrest unwanted momentum. Hence, a false alarm can significantly disrupt the continuation of any daily activities.

Limited Fall Data: True falls in actual living conditions are difficult to record and analyse. Therefore, most studies rely on simulation falls, which do not fully replicate the motion sequence of a true fall. Besides, the successful implementation of a fall intervention solution will further reduce the occurrence of true falls, making the validation of the solution even harder.

To the best of the authors' knowledge, there are only two attempts at robotic fall intervention solutions. Firstly, the BioRobotics Institute of Scuola Superiore Sant'Anna created a pelvis exoskeleton (Active Pelvis Orthosis, APO) for slip recovery [13]. The APO has two pelvic joints that stiffen upon detection of a fall but remains in zero torque mode otherwise. Results showed that the APO reduced the XCoM deviation during a detected slip. Their fall detection algorithm was based on adaptive oscillators that detected deviations from periodic signals. However, it may not be suitable for everyday use as most activities of daily living are not periodic by nature. Besides, stiffening of the lower limbs may not be sufficient for slip recovery as the CoM may already be out of the BoS, leading to a fall. It is also assumed that sufficient friction is present between the foot and the ground for the stiffened joint to maintain the CoM position. However, true slips often occur in slippery environments that even multi-belt treadmills cannot replicate.

Another balance assistive exoskeleton is the MindWalker [14]. This system has three powered joint axes per leg, at the hip abduction/adduction, hip flexion/extension and knee flexion/extension. MindWalker reduced deviations of XCoM [85] from normal motion in the frontal plane by doing hip ab/adduction during swing phase. It has also shown capabilities in assisting weight shifting during the double stance phase. However, they did not account for balance assistance in other planes

Table 2.2: Differences in Fall Solutions

	Fall Prevention	Fall Mitigation	Fall Recovery	Fall Intervention
Device Mobility	✗	✓✓	✗	✓✓
Transparency	✗	✓✓	✓✓	✓
Injury Reduction	✓✓	✓✗	✗	✓✓

of motion. Besides, their method of using XCoM deviations from normal walking for balance assistance is not suitable for daily usage where subjects may need to lean forward to reach objects or bend down slightly. They have also acknowledged that problems existed in aligning the rigid exoskeleton with the user's joints.

2.3.5 Fall Solutions Conclusion

The differences between the difference solutions are listed in Table 2.2. We have identified 3 factors that are critical to a successful fall solution. There are 1) Device mobility, 2) Transparency and 3) Injury Reduction. Device mobility describes the ease of using the device and carrying the device around. Transparency is the interfering effect of the fall solution devices have on the user even it is inactive. Lastly, injury reduction is the device's capability in preventing injury. Each tick in the table represents the effect of the solution listed in the column header, more ticks indicate greater effect. A cross represents no effect. A tick and a cross means that the solution has some devices that assist in listed factor while some do not.

Fall prevention solutions have low mobility and transparency because the solutions are often large and cumbersome to move around. However, this large footprint greatly increases its BoS, which prevents fall injuries from occurring. On the other hand, Fall mitigation solutions have the goal of being easy to carry around and assist only when necessary. Hence, they have high mobility and transparency. Certain fall mitigation solutions such as airbag devices help to alleviate the fall injury severity, while panic buttons do not provide immediate reduction in fall severity. Therefore, fall mitigation has both a cross and tick for the injury reduction factor. Fall recovery solutions are rudimentary as they are mostly a large base to assist the user in recovering. Hence, it has low mobility and do not reduce injury severity. However, fall recovery solutions are fully transparent as they are only employed after a fall impact has occurred. Lastly, fall intervention solutions have high mobility and moderate transparency because these devices are often wearable, but it still affects the user's ease of movement to a certain extent. Nonetheless, fall intervention solutions

aim to intervene before the fall impact has occur, thereby preventing fall injuries.

2.4 Balance Indicators

Balance indicators describe the state of balance of a bipedal system such as bipedal robots or humans. These indicators condense the state of balance in a single variable, whereby balance is achieved when the variable is constrained within a certain boundary. Stable walking gaits can be generated by searching through trajectories that fall within the constraints of the balance indicators.

The different types of balance indicators discussed in this section include:

- Center of Mass / Center of Gravity
- Zero Moment Point
- Center of Pressure
- Capture Point / Extrapolated Center of Mass
- Poincare Map

2.4.1 Center of Mass / Center of Gravity

Center of Mass (CoM) take the sum of all the rigid bodies positional coordinates and divide them by the total mass. The result is a point in the three-dimensional (3D) space where the resultant net moment of all the bodies (in their static state) is zero. The formula for CoM about the x axis is as follows:

$$x_{com} = \frac{1}{M} \sum_{i=1}^n m^i p_{x,com}^i \quad (2.1)$$

where x_{com} is the position of CoM in the x-axis; M is the total mass of the body; n is the total number of rigid bodies; and m^i and $p_{x,com}^i$ is the mass and position (in x-axis) of individual rigid body.

Center of Gravity (CoG) is the same as CoM, only with CoM's vertical axis set to 0. Therefore, CoG will always lie on the horizontal plane. CoG allows for a simple and yet efficient way of determining whether a stationary body will stay upright. If the CoG position is within the BoS of a stationary body, then the body will always remain upright. BoS is an area on the floor with its vertices formed by any part of

the body that are in contact with the floor. An elderly person can increase his/her BoS by using a crutch to extend his/her arm to the floor.

2.4.2 Zero Moment Point

ZMP stability criterion extends on the idea of CoG by accounting for the fact that the body does not stay stationary forever. Instead, forces other than gravity can exist on rigid bodies. Muscles can contract to generate a force that changes the acceleration of the rigid bodies. ZMP specifies a point on the ground where the net moment, body accelerations and GRF from all the dynamic body parts become zero [86, 87]. When the body is static, ZMP equals to CoG. As the body begins to move, its dynamic forces dominate the static forces and ZMP accounts for these dynamical forces.

ZMP is calculated per axis by summing all the moments about that axis (in this case, y axis is used as an example) and equate it to zero:

$$\sum M_{zmp,y} = 0 = \mathbf{p} \times \mathbf{F}_{x,z} \quad (2.2)$$

where $M_{zmp,y}$ is the sum of moments for the Y axis; $\mathbf{F}_{x,z}$ are the vector forces on the x and z axes; $\mathbf{p}$ are the vector moment arms for the corresponding forces. All forces such as GRF have to be included when calculating the summation of moments. Expanding Equation 2.2 gives the following:

$$0 = -(p_x \cdot F_z) + p_z \cdot F_x$$

$$0 = \sum [-p_{x,com}^i (m^i g + m^i \ddot{p}_{z,com}^i) + p_{z,com}^i m^i \ddot{p}_{x,com}^i] - x_{zmp} (Mg + Mp_{z,com}^{\ddot{}}) + z_{zmp} Mp_{x,com}^{\ddot{}}$$

where g is gravitational acceleration at $-9.8ms^{-2}$; $p_{x,com}^i$ and $p_{z,com}^i$ are the distances of each rigid bodies' CoM from origin; $\ddot{p}_{x,com}^i$ and $\ddot{p}_{z,com}^i$ are the accelerations about the corresponding axes; m^i is the mass of each rigid body; M is the total mass of the all the bodies; $p_{x,com}^{\ddot{}}$ and $p_{z,com}^{\ddot{}}$ are acceleration of the combined body's CoM about their corresponding axis. Negative signs occur from the cross product of different axes ($\mathbf{i}_x \times \mathbf{i}_z = -\mathbf{i}_y$ and $\mathbf{i}_z \times \mathbf{i}_x = \mathbf{i}_y$).

z_{zmp} is set to zero because of ZMP projection to ground.

$$0 = \sum [-p_{x,com}^i (m^i g + m^i \ddot{p}_{z,com}^i) + p_{z,com}^i m^i \ddot{p}_{x,com}^i] + x_{zmp} (Mg + Mp_{z,com}^{\ddot{}}) \quad (2.3)$$

Rearranging:

$$x_{zmp}M(g + p_{z,com}^{\ddot{}}) = \sum [p_{x,com}^i m^i (g + p_{z,com}^{\ddot{}}) - p_{z,com}^i m^i p_{x,com}^{\ddot{}}] \quad (2.4)$$

Finally, ZMP is obtained by rearranging the unknown ZMP's x position (x_{zmp}).

$$x_{zmp} = \frac{\sum [p_{x,com}^i m^i (g + p_{z,com}^{\ddot{}})]}{M(g + p_{z,com}^{\ddot{}})} + \frac{\sum (-p_{z,com}^i m^i p_{x,com}^{\ddot{}})}{M(g + p_{z,com}^{\ddot{}})} \quad (2.5)$$

If there is only a single body, then x_{zmp} simplifies to

$$x_{zmp} = x_{com} - \frac{(z_{com} p_{x,com}^{\ddot{}})}{(g + p_{z,com}^{\ddot{}})} \quad (2.6)$$

Similarly for y axis:

$$y_{zmp} = y_{com} - \frac{(z_{com} p_{y,com}^{\ddot{}})}{(g + p_{z,com}^{\ddot{}})} \quad (2.7)$$

ZMP is generally used as a stability criterion in motion trajectory synthesis for bipedal walking robots. The most famous being Honda's ASIMO bipedal robot [88]. The ZMP criterion can be stated as :*Given desired state variable trajectories that are consistent with the dynamics, and that predict the ZMP staying inside the BoS, a trajectory tracking control algorithm can stably track those trajectories as long as the ZMP does indeed remain inside the BoS.* That is, as long as the ZMP lies strictly inside the BoS of the foot, then these desired trajectories are dynamically feasible. However, it does not constrain the robot to a non-falling condition, as zero force does not mean zero velocity.

Multiple studies have also shown that maintaining the ZMP inside the BoS (ZMP criterion) is not a necessary condition for stable walking [87, 89]. This observation can be seen on passive dynamic walkers [90] and point feet robots where the ZMP is always outside the BoS during single support phase [89].

2.4.3 Center of Pressure

Centre of Pressure (CoP) is defined as a point under the foot where just a single force vector can represent the total sum of the pressure field at the CoP point. CoP can be expressed as:

$$CoP = \frac{\int \mathbf{p} F(\mathbf{p}) d\mathbf{p}}{\int F(\mathbf{p}) d\mathbf{p}} \quad (2.8)$$

where $\mathbf{p}$ is the positional vector of any point on the ground; $F(\mathbf{p})$ is the localised pressure/force at the position $\mathbf{p}$. During actual CoP implementation, CoP is measured from force sensors in the foot by force plates. CoP and ZMP are on the same point when the ZMP lies inside the BoS. However, when ZMP is outside the edge of the BoS, CoP will diverge from ZMP as CoP is a physical point on the base of the robot/human. On the contrary, ZMP and CoG are both virtual points on the ground. When CoP and ZMP diverge, the biped will start leaning in the direction of the CoP-ZMP vector.

2.4.4 Capture Point

CP is defined as a point that can be stepped to, in order to reduce the CoM velocity to zero [87]. The goal is to find a point on the ground that will lead to zero overall velocity. It is built upon the simple LIPM to eliminate the kinetic energy. LIPM is a model of the bipedal robot using the dynamics of an inverted pendulum, but with a constant vertical height [91].

Figure 2.7: Parameters for calculation of the CP based on a LIPM. CP = Capture point, h_0 = height of pendulum (constant), x_0 = initial position of CoM, r_x = distance of CoM to CP.

Derivation of CP starts with the assumption that there are only gravitational force and a linear force (F_x) acting on the LIPM (Figure 2.7). By calculating the sum of moments about the CP:

$$F_x h_0 = M g p_x \quad (2.9)$$

Where M is mass of the pendulum, g is the gravity constant ($-9.8ms^{-2}$), F_x is the horizontal linear force acting on the pendulum at that time instant, h_0 is the pendulum height which is constant for LIPM and p_x is the distance from CoM to CP.

Total energy for the CoM to move from the current position to the CP would be:

$$\int F_x dp_x = \int \frac{Mg}{h_0} p_x dp_x = \int \frac{Mg}{h_0} (x_{com} - x_{CP}) dp_x = \frac{Mg}{2h_0} p_x^2 \quad (2.10)$$

Since energy equals to force multiply by the distance moved, and we want to eliminate all sources of kinetic energy from the system; we equate the energy from moving the CoM to the pivot, to the horizontal kinetic energy that exists in the system:

$$\frac{1}{2} M v^2 = \frac{Mg}{2h_0} p_x^2 \quad (2.11)$$

where v is the linear velocity of the CoM. Solving for p_x , which is the distance of CP from CoM:

$$p_x = \sqrt{\frac{h_0}{g}} v \quad (2.12)$$

Using a LIPM for our model simplifies our calculation significantly [92], as a normal inverted pendulum will cause Equation 2.9 to be a non-linear equation as h_0 will change as p_x changes. The constant height assumption for LIPM is valid because a human walks with its CoM at around the same height. This is because the trunk muscle attenuates the vertical acceleration to achieve stable optic flow and vestibular signal [18].

Since the capture point is only an estimation for the LIPM, Pratt *et al.* [87] defined what is known as a capture region: *A capture region is an area around a capture point which allows the biped to retain its stability.* By allowing the biped to lunge its body forward or windmilling its arm, the internal angular momentum around the CoM changes, creating a region around the capture point where the biped can move its body without moving its legs to retain its balance. Applying ankle torque will also create a region around the capture point while providing means for the biped to minimally regulate its CoP such that it falls into the BoS without using the large reserve angular momentum of the upper body unnecessarily. The calculation of the capture region can be found in the Pratt *et al.* paper [87].

It must be noted that the CP might not be reachable in one step because of the leg length and/or leg velocity limitation. In this scenario, once the swing foot lands on the ground, a new CP must be calculated. A fall will be inevitable if the CP distance from CoM increases faster than the achievable speed of the swing leg.

Extrapolated Center of Mass

The idea of Extrapolated Center of Mass (XCoM) is identical to Capture Point (CP), but was independently developed by another research group [93]. However, the paper on CP provided a more robust study on the capture region, whereas XCoM did not include a region whereby balance can be achieved without moving the legs.

Zero Moment Point vs Capture Point

ZMP is calculated based on the dynamical forces acting upon the body, whereas CP is based on the kinetic energy present on the body. Therefore, ZMP is useful in scenarios where there might be external forces acting on the body. CP needs to be calculated every time any external force adds energy into the system. However, ZMP does not adequately describe a stable gait, as explained in Section 2.4.2. While CP also does not adequately describe a stable gait due to its assumption, it is more representative of a normal human gait. Hence, CP can be used to generate trajectories or measure instability during unperturbed gait. On the contrary, ZMP is useful during perturbation to generate a suitable course of action.

2.4.5 Poincare Map

Poincare Map is more of a tool that helps to visualise a periodic gait than a balance indicator. Stable trajectories will cycle and return to ideally the same point in a slice of state space (surface of the section) (Figure 2.8). By studying the deviations of the Poincare map, one can determine a suitable state of the system to return the system to periodicity [87].

Figure 2.8: (Left) Phase plot of a Van der Pol oscillator with the surface of the section shown with a black dashed line. (Right) The resulting Poincare return map (blue) and the line of slope one. The intersection of the return map and slope of one represent a velocity where a steady periodic gait can be achieved. Image obtained from Tedrake [94]

The usage of the Poincare map as a stability assessment tool is to determine if the current path of action (trajectory) will lead back to the same stable state. If the planned trajectory can lead back to the same upright walking state, then the trajectory is stable. However, the Poincare map does not allow for uneven terrain or even a slightly higher perturbation, causing it to be limited to periodicity analysis. Since most of the natural human walking does not require periodicity, the Poincare map has limited applications [87].

2.5 Pre-Impact Fall Detection

Given the absence of detailed and comprehensive human and human-exoskeleton combined models, the balance indicators stated in Section 2.4 cannot be relied upon to detect instability. Details on why balance indicators cannot be used for fall detection are described below:

Lack of accurate joints and bodies information: It is nearly impossible to obtain an accurate model of the CoM and inertia tensor of a living human subject. Besides, environmental factors such as fatigue, diet and injuries cause a change in model parameters in real-time. Such model inaccuracies cause noise in the control algorithm, which in turn accumulate over time, leading to system instabilities.

Muscle models cannot be fully replicated: Unlike mechanical actuators, human muscles experience fatigue and changes in CoM. This ever-changing actuator prevents a predictive model from being developed, and hence hinders the creation of an accurate fall assessment protocol.

Human motion can be unpredictable: Even if joints, bodies and muscles are perfectly modelled, the human brain reacts differently among individuals and under different scenarios. These make it difficult to create control algorithms that can perfectly assist in the all intended motion.

Human walking is already falling: Human walking has been optimised such that the middle of the swing phase is detected as falling; even by the balance indicators described in Section 2.4. It is therefore also not possible to use those balance indicators to detect true dangerous fall.

Therefore, fall detection algorithms rely on other indicators, such as excessive dynamical forces and anomalies to detect instability. This section begins by dis-

cussing the different types of sensors and their placements. Next, each of the different types of algorithms will be categorised based on their methods, with discussion on each of their advantages and disadvantages.

2.5.1 Sensor Types

Existing fall detection relies mostly on ambient sensors or wearable sensors [95]. Ambient sensors are unobtrusive as the sensors are integrated into the environment, such as cameras [96], microphones [97] and sensors that detect floor vibration [98] or pressure [99]. However, these sensors are immovable and redundant once the subject travels beyond the predefined environment.

On the other hand, wearable sensors are always attached to the subject's body, allowing for constant monitoring. Inertial Measurement Units (IMUs) that consists of a combination of three axis accelerometer, three axis gyroscope and three axis magnetometer are the common choice for the wearable sensors [95]. These IMUs are small in size and use relatively little power as compared to cameras and microphones. A barometer can be included within an IMU to improve fall detection accuracy [81].

Unfortunately, IMUs face a well-known problem of drifting and noise. Drifting occurs when position estimation is extracted from the IMUs. Since IMUs can only measure acceleration and angular velocity, positional data are estimated using integrations. This implies that noise that exists in the IMU data is accumulated over time, leading to significant positional errors. Additionally, the magnetometer is highly susceptible to ferrous material in the environment. With the abundance of steel and iron around, the chances of magnetometer being invariant in all its use scenarios are rare. Therefore, fall detection algorithms that rely on IMUs commonly do not use positional data for analysis. Even though there are drawbacks to the IMU technology, it remains the most popular form of fall detection device as it allows for great mobility.

2.5.2 Basic Feature Thresholding with Logic Tree

This section describes methods and algorithms that apply a threshold constraint on any basic features such as altitude, accelerations, velocity and position. These features can undergo averaging or filtering before being used as inputs to the threshold constraint. Extracted features that require complex calculations such as Fast Fourier Transform are not included in this section.

A simple vertical velocity thresholding method has been used as a pre-impact fall detection [100]. An IMU mounted on the waist collects the acceleration data which was rotated and integrated to give velocity. The maximum vertical velocity during ADL is used as the threshold for fall detection. They reported that an individualised threshold detected all simulated falls with 100% accuracy (100% specificity and 100% sensitivity) and detection time of 70 – 375ms before impact. Although this study included multiple ADLs for rigorous comparison (such as walking, stairs climbing, sitting/lying down and standing up), their falls were self-simulated from a quiet standing position and then falling forward, backwards, sideways and downwards after a trigger from an external push. These stimulated falls are not representative of real-world falls as most falls occur during the midst of an ADL. Furthermore, the external push would have imparted a sharp increase in momentum, which skews the results towards having a higher chance of type one error. Another study used a similar thresholding technique with Wu *et al.* [100] using a chest mounted IMU [101]. Their subjects were also standing still before simulating a fall onto crash mats. They reported a similar 100% accuracy (100% specificity and 100% sensitivity) with a detection time of $323 \pm 66.1ms$ before impact.

Angular velocity has also been used to detect falls with promising results [102]. Multiple IMUs were placed at the sternum and frontal waist to detect sideway falls and the right underarm for backward falls. Peak ADLs angular velocities were chosen as the respective IMU threshold for fall detection. They reported a sensitivity of 100%, a specificity of 97.5% and detection time of $100 \pm 50ms$ before impact for backward falls; and a sensitivity of 100%, specificity of 94% and detection time of $140 \pm 90ms$ before impact for sideway falls. Similar to the majority of other studies mentioned above, this study also used simulated falls from silent standing, which fail to represent real falls.

A combination of vertical and horizontal trunk velocity can also be used to differentiate falls from other ADLs [103]. It was noted that during ADLs, the increase of horizontal and vertical velocities are mutually exclusive. However, both horizontal and vertical velocities increased together dramatically during a fall, at 300 – 400ms before impact. In spite of the excellent results, the study only used simulated falls that were initiated from a silent standing position. These falls are not representative of real falls.

Correlation between the kinematics of fall datasets and collected data can also be used for fall detection [104]. A study has used a preliminary ± 10 deg threshold value to detect an anomaly. Upon detection, the correlation between the flexion

angle of the thigh and torso, and the correlation between the thigh and a previously recorded reference fall data were matched. A fall was then detected if the similarities among the 2 correlation relations were high [104]. They reported 100% specificity, 95.2% sensitivity and a mean detection lead time of $700ms$. Two main problems can be identified with this fall detection approach. Firstly, correlation with reference fall signals is not a good indicator because real falls are mixed with similar actions that consist of similar signals of lower magnitude to the reference signals. The study also uses simulated falls from silent standing that does not represent true falls.

2.5.3 Movement Classification Techniques

Support Vector Machine

Support Vector Machine (SVM) is a form of supervised machine learning methods that separates data into two categories. Kernels that map the input data into higher dimensional spaces allow for separation of data with a gap as wide as possible. In the applications of fall detection, SVM allows for the separation of ADLs and falls based on their corresponding observed data.

One study used sensor combinations of 7 different IMUs to determine the best combination for fall detection [105]. For each IMU, the mean and variance of accelerations and angular velocity from a 2.5 seconds window before fall impact was used as input into the SVM. The result showed that SVM is capable of obtaining 100% sensitivity and 100% specificity. However, the SVM was not implemented in real time; hence, the mean detection time is not known. Additionally, the falls included in this study were acted out by the subjects after observation of video recordings from actual fall. These falls do not have a sudden increase in momentum that is only seen in real falls.

Given that the performance of SVM is highly dependent on the input features, another study [106] chose 2 of the most contrasting features as inputs to a SVM and also obtained 100% sensitivity and 100% specificity with $203.59ms$ of mean detection lead time. However, they did not mention which features were specifically chosen, and their falls were simulated from silent standing, which is unrepresentative of real falls. Principal Component Analysis (PCA) and Independent Component Analysis (ICA) can also be used to choose and reduce the dimension of input features to improve the performance of SVM [77].

Although SVM may be useful in separating ADLs from falls, it requires a large sample size of true falls, which is challenging to collect. Hence, it may not be a

suitable method for designing a fall detection algorithm.

Discriminant Analysis

Discriminant Analysis (DA) is an analytical method that separates data into different categories. It assumes that each of the separated categories is of normal distribution and has the same variance.

A study made use of mean acceleration and variance of each axis from different combinations of 5 motion capture markers (both ankles, sternum and top of the head) as input into a Linear Discriminant Analysis (LDA) [107]. They reported a best marker combination of both ankles and sternum at a sensitivity of 96% and specificity of 97%. No mean detection time was reported as the study made use of a fixed 1.5 seconds window before the impact to detect train the LDA. The fall dataset was collected from subjects that mimicked the elderly falling captured from video recordings.

Quadratic Discriminant Analysis (QDA) improves upon LDA by allowing for separation boundaries between categories to be non-linear and, hence higher discrimination power. QDA has been used to classify ADLs from falls using only the trunk's angular velocity and flexion angle [108]. A sensitivity of 100%, specificity of 95% and $255 \pm 22ms$ mean detection time was reported. The study only conducted slip fall, which does not contain all fall types. However, their slip trials were conducted while walking on slippery surfaces, which is more representative of a true slip than the majority of the fall trials conducted by other fall detection studies.

DA faces similar problems with SVM, in that both methods require large amounts of both ADLs and fall data to accurately identify falls. Hence, classification techniques are generally not suitable for fall detection algorithms.

Neural Network

Neural Networks Neural Network (NN)s has the capabilities to classify or identify anomalies given sufficient dataset. However, their performance and processing time greatly depend on the architecture of the network. Since the understanding of the inner workings of NN is still largely unknown, users commonly pass a large amount of inputs into the NN. This method is often feasible when real-time performance is not sensitive. However, this is not the case for pre-impact fall detection. Hence most NN for fall detection is often accompanied by feature extraction and dimension reduction.

A study has made use of ICA together with NN for fall detection [109]. Among acceleration vectors from 15 motion captured segments, they identified that the hands and feet contained the most information with ICA. The reduced features from ICA was then inputted into a 3 layer, 80 neurons feed forward NN. The NN was set to classify the inputs into 3 different categories, (1) Walking, (2) Perturbation and (3) uncertainty. The accelerations input from the combined 15 markers produced the best results at a sensitivity of 92.7% and specificity of 98.0% with a mean detection time of $351 \pm 123ms$. The marker set combinations with the most information identified by ICA had an inferior result of 92.1% sensitivity, 96.3% specificity and a mean detection time of $346 \pm 121ms$. It should be noted that the algorithm was validated on treadmill induced slips versus walking only, without other ADLs and other kinds of falls.

Hidden Markov Model

HMM is a doubly embedded stochastic process, having the capability to detect both fast and slow near-falls. It does so by clustering the input (observations) into different hidden states and obtaining the most probable sequence of hidden states given a sequence of observations. As a result, it allows for the classification of events of states that cannot be directly observed based on historical data. In our scenario, where gait pattern cannot be easily classified and observed, HMM is a great tool for identifying motion types. Observations input into the HMM require the kinematics data obtained from the user's motion.

HMM can be separated into two kinds: (1) Discrete and (2) Continuous. In discrete HMM, observations belong to discrete groups which are then soft assigned (emission probabilities) to the hidden states. It has been used in fall detection with a single 3-axis accelerometer on the chest as its input signal [110]. Frontal and side-way falls were acted out by subjects onto a thick sponge mat. The magnitude of the accelerometer was classified discretely into eight different clusters based on different range, and were capable of obtaining 100% sensitivity, 88.75% specificity and 200 – 400ms before impact detection latency.

In Continuous Hidden Markov Models (CHMM), observations are modelled as continuous probability density functions which are then soft assigned to different hidden states. One study reported fall detection of 98% sensitivity and 100% specificity by using the first ten coefficients of Fast Fourier Transform (FFT) from each axis of the chest mounted accelerometer and gyroscope as the CHMM inputs[111].

Their subjects simulated lateral falls from a quiet standing posture. Another study reported 95.33% sensitivity and 97.66% specificity by using different fall detection methods for static and dynamic motion [112]. Simple threshold detection of chest acceleration values was used for static fall detection, while CHMM were used to identify falls from dynamic motion using surface Electromyography (EMG) and torso plus right thigh acceleration data. CHMM has also been combined with One-Class Support Vector Machine (SVM) to increase its detection accuracy, but the sensitivity and specificity data have not been reported [113].

All algorithms mentioned above create one HMM per motion type, but that is not ideal for real-time fall detection. Multiple HMM are computationally expensive and hence increases the detection latency.

Classification Techniques Conclusion

All classification techniques are based on finding a hyperplane plane with a maximal margin between each category or class. This implies that there is a need to have an abundance of data for the categories to be classified accurately. Given that it is highly difficult to collect real fall data, the rationale for using classification techniques as fall detection algorithms remains weak.

2.5.4 Anomaly Detection

One-Class SVM

One-class SVM extends upon the traditional SVM by minimising the enclosed hypersphere around the normal training data. In the perspective of the current project, the normal training data are features extracted from ADL. Fall features outside of the hypersphere get flagged as an anomalies.

The feasibility of one-class SVM has been evaluated as a fall detection algorithm [114]. Although the study did not propose a pre-impact detection, it highlighted the potential of one-class SVM as anomaly detection. A single tri-axial accelerometer was placed on the waist of a subject, while fall scenarios and ADLs were performed. Input features to the one-class SVM included the time interval from fall onset to impact, average and variance of acceleration, the interval of debounce, average and variance of debouncing acceleration. They reported a sensitivity of 97.76% and a specificity of 95%.

The accuracy of all SVM depends significantly on the input features; hence, caution must be taken when training the SVM with ADLs.

2.5.5 Fall Detection Conclusion

Thresholding methods are easy to execute and fast, but any changes in the ADLs or falls motion may render the whole logic and threshold ineffective. Examples of motion that are normally not included in studies include sitting down quickly, taking the elevator and stairs climbing/lowering. These actions exhibit large accelerations and angular velocity that easily exceed the thresholds for fall detection. Hence, a fall detection algorithm that is general for all kinds of ADLs should be easy to tune and adjust for individualisation and inclusion of new unknown motion.

Classification techniques are based on finding a hyperplane plane with a maximal margin between each category or class. This implies that there is a need to have an abundance of data for the categories to be classified accurately. Given that it is highly challenging to collect real fall data, the rationale for using classification techniques as fall detection algorithms remains weak.

On the contrary, anomaly detection is useful in the current context, whereby the number of true and accurate fall data can be minimal. Anomaly detection techniques are also easy to retrain and include motion that are previously excluded.

Majority of the reviewed fall detection algorithms also depended on simulated falls that were preceded immediately by silent standing and followed by an impact with a soft ground surface. Such fall does not represent any of the true fall scenarios as subjects are instructed to fall like a piece of log. Falling like a log considerably simplify the fall scenarios, as recovery motion and their preceding actions reduce the contrast between fall and non-fall scenarios.

2.6 Soft robotics

Soft robotics is a relatively new field in robotics that aims to make use of robots, actuators and sensors that are soft and flexible to navigate around tight areas, conform to surface contours and/or to perform other tasks not possible with rigid components. These systems are normally also lightweight and require no joint alignment between the actuators and human.

Recently, there have been some advancements in the rehabilitation field using soft robotic actuators. The most common types include hand and legs assistance devices using either pneumatic or cable driven actuators. Pneumatic and cable driven actuators are "soft" because they are flexible and more importantly, they can exert forces over weird angles and longer distances than rigid actuators.

In this section, the two most common types of soft robotic actuators are discussed: Pneumatic and Cable driven actuators. Other types of soft robotic actuators not included are: Dielectric elastomer [115], Shape Memory Alloy [116] and Combustion Driven Actuators [117]. The sensor technology used in soft robotics is also discussed, followed by soft robotics applications in rehabilitation.

2.6.1 Actuators

Pneumatic Actuators

Pneumatic Artificial Muscle (PAM) is probably the most well known and common type of soft actuators. They are also called pneumatic actuators or McKibben's muscles, and they work by radially expanding and longitudinally contracting when air is being pumped into them (Figure 2.9). This contraction is caused by the inner expandable tubing pushing against an outer non-extensible braided mesh.

Figure 2.9: A Festo fluidic muscle that contracts to 75% of its original length when fully inflated.

The advantage of PAMs is their high force to weight ratio and high power to volume ratio (about five times higher in comparison to an electric motor or hydraulic actuators) making their performance similar to human muscles [118]. Additionally, PAMs have a high level of compliance, making them safer for human-machine interface devices. However, compliance implies that PAMs are relatively inaccurate and difficult to control as compared to their rigid actuators counterparts. Moreover, PAMs performance analysis typically does not include the weight and power consumption of the mandatory gas pump in the total system, skewing the real force to weight ratio.

Modelling the PAMs system also proved to be a very challenging task due to its the multitude of factors surrounding the fabrication of PAMs such as the thickness of the mesh and elastic tubing, and the anisotropic properties of the mesh. The dynamics of the airflow and friction between different components within the PAMs during different scenarios also hindered the development of the models [118–120].

A new kind of PAM called Soft Pneumatic Actuators (SPA) is gaining traction in the research world. It is made entirely out of soft silicone material. SPA can expand in a variety of configurations by arranging how the individual air compartment and stiffer materials are located. Joining multiple SPA together formed PneuNets that generate torques rather than linear motion [121, 122]. Combining materials with different stiffness on the surface of SPA can also generate torsional moments [123].

Bowden Cable Actuator

Bowden cable actuator depends on an external sheath to minimise unwanted compression along a route path while shortening the inner cable to transfer a pulling force over a long distance (Figure 2.10). The efficiency of Bowden transmission is significantly affected by friction along the length of the sheath such as static and dynamic friction, viscous friction and stick-slip phenomenon [124]. The transmission efficiency of a Bowden cable actuator can range from 50% to 70% [125].

Proper implementation of the Bowden cable actuator requires both ends of the Bowden cable to be fixed. The top end is fixed to an attachment site, near an actuator (electric motor), while the other end is at another attachment site near the end effector. Care must be given to the maximum, and minimum actuation distance as the exposed length of the cable must be able to accommodate that variable length.

Figure 2.10: Bowden cable actuator uses a nearly incompressible Bowden sheath with an inner cable to pull on another object at the distal end while passing through a complex pathway. Both ends of the sheath must be attached for the actuator to function properly.

Several factors affect the performance of the cable [124]:

- Normal forces on the cable (significant in regions of high curvature)
- friction coefficients of both contacting materials

- velocity of the cable during operation

These forces can be directly or indirectly reduced by decreasing the cable wrapping angle, decreasing the friction coefficients of sheath and cable, and pre-tensioning the cable. However, reducing the pre-tension might introduce problems like cable detachment from their pulleys.

2.6.2 Soft Sensors

Sensors are used to supply information about position/orientation or force/torque back to the controller as feedback signals. Previous implementations of position feedback were done through sensors such as motion capture cameras with reflective markers, goniometer, linear variable differential transformer, rotary variable differential transformer, and linear/rotary encoders. Force sensors are mostly implemented as pressure sensors over a fixed area which outputs resistance or capacitance, whereas torque sensors are normally done using hall sensors or strain gauges.

Similarly, rigid sensors are no longer suitable for use on soft tissues as they impede the motion and reduce comfort of the users. Furthermore, they can also be used on conventional rigid exoskeleton.

Embedded Microchannel Sensors

Flexible embedded microchannel silicone sensors have recently been developed by Park et al. [126]. They made use of micro-channels filled with conductive eutectic gallium-indium (EGaIn) liquid that changes in their geometry when compressed to create a change in resistance (Figure 2.11). By changing the printed channel's shape, the sensors can be made to sense forces in different directions and magnitudes [126, 127].

Air-pack Sensor

Air-pack sensor has many similarities to the pneumatic actuated muscles, but instead of actuation, it is used for sensing. An inelastic air-pack which is connected to a pressure sensor is placed between 2 compressing surfaces such as between the shoe insole and the base of the shoe. This allows for consistent pressure measurement while not constraining the flexibility of the surfaces. Examples of such systems are AMI air-pack, PicoPress (Figure 2.12), and Talley Skin Pressure Evaluator. However, many of them are no longer in production or are only available on request for research purposes.

Figure 2.11: Soft EGaIn sensors. Geometry made for pressure sensing (top left), pressure and strain sensing (top right, bottom left), shear pressure (bottom right). Image obtained from [126, 127].

Figure 2.12: An air pack is placed between 2 compressing surfaces to measure pressure changes due to deformity.

Resistive Pressure Pads

These resistive pressure pads are formed from 2 sheets of thin polyester, each coated with linear conductors that are enclosed in a pressure sensitive material. As the resistivity of the centre material changes in response to the applied pressure, the two layers of conductors recognise the change and create a matrix of the sensing location. Examples are the Tekscan I-scan System (Figure 2.13).

Resistive Force Sensors

Another use for pressure sensitive resistive surfaces involves force sensors. These sensors lack the intricate sensing matrix of the pressure pad, but have the advantage of being able to have a larger pressure resolution. One example is the Tekscan Flexiforce sensor.

Figure 2.13: A resistive pressure pad (I-Scan) made by Tekscan.

Smart Braid: An application for the resistive force sensor is the smart braid. Felt *et al.* [128] made a soft sensor specific for PAM. In particular, the mesh that surrounds the inner tubing of the PAMs were made out of wires (Figure 2.14). When this mesh expands due to the expansion of the inner tubing, the inductance and resistance of the circuit changes. This technique allowed for measurements of up to 0.5mm or 5N resolutions.

Figure 2.14: Smart Braid air muscles. The braids of the mesh surrounding the PAMs are made of a single length of wire. The current of the braids flows in a single direction (a). Inductance increases when PAM contracts, bringing the wires closer (b). A larger load increases the strain on the wires and hence, increasing the resistance (c). Image obtained from [128].

2.6.3 Soft Robotics Rehabilitation Applications

Soft robotics are soft and lightweight which are ideal for use in rehabilitation devices as they provides better user comfort and also reduce the energy consumption of both system actuators and the user. This is especially important, as the metabolic cost of the user increases by 7.5 – 8.5% when an extra kilogram of weight is added to the legs, and 1 – 2% when added to the waist [129, 130].

The inherent material compliance also eliminated joint misalignment and discomfort issues [131]. Rigid exoskeletons that depended on braces to secure their joint positions on the users caused shear and normal pressure, which can be damaging to the skin and thus, reducing acceptability [132].

In this section, applications are reviewed according to the site of application of the soft robotics technologies. They are further separated into upper limbs, lower limbs and the torso.

Upper Limbs

Hands rehabilitation mostly aimed to increase the grasping ability of the patients, such that various ADLs can be performed with greater ease. These ADLs include bathing, dressing, feeding, toileting, mobility, and transferring themselves [133]. Soft technology aims to improve the dexterity of the fingers, which aids in for complex grasping critical for everyday tasks.

Hyunki *et al.* [134] developed a cable-driven glove that can be worn comfortably by stroke patients to assist them in performing basic hand and finger function. The Bowden cables employed in their design were capable of actuating multiple fingers together as they routed a single cable through 2 fingers using low friction Teflon tubings. By tensioning the cable, two fingers were assisted to flex together. The placement of the Teflon tubings, which acted as the routing anchors, was critical as they determined the moment arm and resultant posture of the fingers. Polygerinos *et al.* [135] created a similar glove for assisting in fingers movement. However, they made use of PneuNets to generate bending moments which directly transfer the force onto the fingers. Motion was generated by pumping water into the PneuNets which expanded radially.

Lower Limbs

As opposed to upper limbs rehabilitation devices which focuses on dexterity, lower limbs devices require much higher strength and speed to create a normal walking

Figure 2.15: Cable Driven glove (Exo-Glove) [134] (left) and PneuNets driven glove [135] (right).

gait and assist in fall recovery motion.

Asbeck *et al.* [136, 137] created a cable driven lower-limb exosuit that provided both hip flexion and ankle plantar-flexion torques with only one motor, thereby reducing the overall system’s weight and power consumption. This was made possible by joint synergies that occurred during walking. They also introduced the concept of anchor points and virtual anchor points. Anchor points were responsible for transferring tensile forces to the body whereas virtual anchor points were routing points that directed the tensile forces along desired paths and terminated at anchor points. Routing the tensile forces through the centre of the knee (virtual anchor point) allowed for minimisation of undesirable knee moments while supplying torques to both the hip and ankle [136]. In addition, the suit was also made up of webbings, which formed the underlying structure of the exosuit. The webbings provided attachment sites for the anchor points and increased body stiffness and user’s comfort [138]. Overall, they reported an average metabolic energy reduction of 6.4% for a powered suit versus an unpowered suit.

Pneumatic actuators have also been used on lower limbs exoskeletons. Kawamura *et al.* [139] developed a hip flexion assistive exoskeleton that used a proprietary latex rubber inner tubing which was surrounded by a straight carbon-fibre sheet (unlike the conventional mesh). The straight fibres allowed for larger contraction force and velocity. Their experimental results showed that the targeted muscle has reduced EMG activation, but the remaining abduction/adduction muscles ended up with increased excitation to maintain body balance. Asbeck *et al.* [136, 137] did not mention this problem even though it was highly likely that they experience it as well. This problem could be solved if the routing of the PAMs followed the actual routing of muscles and tendons. This solution has been implemented by Park *et al.* [140], but they did not report the performance of their design on actual walking. Another study with PAM was conducted by Wehner *et al.* with their proprietary

Figure 2.16: Cable driven, multi-articular exosuit [137]. Actuation is provided using a single motor for both leg's hip flexion and ankle plantarflexion. Another motor provides hip extension for both leg.

PAMs [141]. They designed a 6 DoF (sagittal plane hip, knee and ankle) exoskeleton that can achieve similar metabolic consumption when compared to not having any load on the body. However, like the rest of the pneumatic dependent system, they also did not include the mass of the pump and power source in their calculation of system weight and efficiency.

Torso

Torso actuation is rarely seen in literature as the curvature of the back changes during flexion, making it difficult to create a form-fitting exoskeleton. Additionally, the high mass and small moment arm of the torso requires a large torque for effective actuation. Therefore, torso exoskeleton or exosuit is rarely targeted. Nonetheless, some groups have ventured into this area with the help of soft robotics.

Tanaka *et al.* [142] developed a cable-driven smart suit that pulled on the user's shoulder through Bowden cable. It only performed lumbosacral extension as its target audience were agriculture farmers who need to bend forward the whole day. Limited information is available as it is published in a Japanese conference. However, they later developed the suit into a passive Smart Suit Lite (SSL) for use with hospital workers [143].

An interesting rigid exoskeleton counterpart is a Stewart platform assembly with multiple layers to allow for lumbar motion [144]. It used linear actuators to form a Stewart platform assembly with multiple layers to account for the changing spine

curvature during motion. The exoskeleton aimed to help correct patients with abnormal posture during the treatment of the human spine.

Figure 2.17: (a) Smart suit with Bowden cable to help in lumbar extension [142]. (b) Dynamic brace for patients with bad postures by [144].

2.7 Fall Inducing Platforms

Fall detection requires the collection of true fall data. However, that is often not possible due to the randomness and unpredictable nature of fall. Majority of the falls simulated in studies mentioned under Section 2.5 were performed from a silent standing posture. Although silent standing posture eases the evaluation of fall dynamics by providing a significant contrast to the upcoming fall, they hardly replicate the true fall scenarios. Falls often occurs during the process of performing another ADL, and these ADLs produce dynamics that significantly decreases the contrast between stable and unstable conditions. Moreover, true effective walking is often described as controlled falling and thus, blurring the differences between fall and non-fall scenarios. Hence, protocols or systems that can replicate true falls as much as possible are vital in all fall studies.

Several efforts have been made to create systems for fall induction. These includes: 1) treadmill-based sudden appearance of obstacle [145], 2) overground-based sudden appearance of obstacle [49, 146–149] or sink-hole [16], 3) sudden braking of rope attached to leg [16], and 4) static treadmill based perturbation [150]. However, all of these systems above are restricted to a certain area for imposing perturbations, limiting the usability of the system. Subjects must keep to a certain narrow pathway, and the ground conditions cannot be changed for different test environments. In addition, the triggers for perturbation depended on a closely spaced force plate [49, 148], or were manually initiated by the investigators [16, 145–147]. This inad-

vertently constrains the subject to walk at a certain speed, as any speed changes would cause investigators to miss the timing for perturbation, or miss the obstacle from a fixed distance force plate.

Figure 2.18: The balance assessment robot provides 3 passive DoF and 3 active DoFs that allows for anterior/posterior displacement, medial/lateral displacement and clockwise/anti-clockwise rotation.

To the best of the author's knowledge, only one robot that does not constrain the user at a specific area and limit the subject's speed has previously been created [151] (Figure 2.18). However, this robot induced fall-like imbalance by providing perturbation at the pelvis, and this led to several problems. Firstly, it is known that the perturbed leg involuntarily stiffens and also initiates responses on the contralateral leg [145]. Pelvis perturbation ignores the effects caused by this stretch reflex as it changes the signalling pathway, leading to different synchronisation of responses. Secondly, changes in the dynamics of the lower limbs caused by obstacles and slippery surfaces are disregarded. These changes affect the outcome of the fall recovery strategies. For example, a leg that encountered an obstacle during a trip will experience sudden deceleration and hence, the user would require more time to widen their BoS. In the pelvis perturbation robot, forward perturbation helps the user to widen their BoS, which improving stability.

A system where falls are repeatable and consistent requires a gait phase detection algorithm. This is because the strategy employed upon a fall is different for various gait phases [49, 53]. Even if a fall can be induced manually by anticipating the gait phase, it is difficult to ensure consistency, which results in a need to collect more fall data. Collecting more fall data increases the subject's risk of danger and even data reliability when fatigue sets in.

2.7.1 Overground VS Treadmill Walking

Overground walking is preferred over treadmill walking even though it is much easier to experiment a treadmill. First and foremost, treadmill walking must kinematically and biomechanically be the same as overground walking for human gait studies to be valid when conducted on a treadmill. Multiple studies have found that there were significant differences for sagittal plane hip and knee kinematics [152–154]. In addition, joints moments and muscular activation, which are critical to the study of biomechanics were also found to be different [155, 156]. The metabolic expenditure of treadmill was also found to be higher than overground walking[154].

In the study of falls, the treadmill is even more unfeasible. Upon a trip, it is an insurmountable task to estimate the speed at which the treadmill should stop to mimic a real fall. Any error in speed estimation induces unwanted dynamics that may assist or hinder the natural recovery motion. A true slip occurs because of low to zero friction that allows the foot to slide over the ground. Split-belt treadmill such as SENLY [157] can provide the initial acceleration of the foot due to floor slippage, but the recovery motion continues on the same slippery surface that is not replicable on the high friction treadmill.

However, treadmill walking does have some critical advantages over overground walking. The most important advantage is that the treadmill provides the function of speed control. Gait velocity affects a multitude of kinematic and dynamic variables that make it the most critical condition when choosing a treadmill over overground. Treadmill also allows for long distance walking in a constraint location, which is not possible for overground walking.

Therefore, when one needs to study the natural gait of healthy subjects, it is suggested to perform overground walking. On the other hand, rehabilitation can be performed on a treadmill as one can still replicate most of the regular gait pattern while retaining the intrinsic treadmill advantages.

2.8 Gait detection algorithm

Gait phase can be separated into several segments. One method of segmentation is shown in Figure 2.19.

Gait phase detection is done conventionally using ground reaction force/pressure sensors to measure changes during stance phase, and using IMU for swing phase [159–163]. The force/pressure sensors can be made up of microswitches, a

Figure 2.19: Different gait phases according to Whittle [158]. Image obtained from Rueterbories *et al.* [159].

small air-bag or resistive sensors [159]. This allows for accurate stance phase identification, but it requires specialised shoes and setup that limits its usage. Hence an IMU-only based system is preferred for its less elaborate setup.

Common IMU-only studies rely on HMM to detect gait phase [164–166]. However, HMM has the flaw of being accurate mostly for cyclic motion. HMM can represent non-cyclic motion, but it requires lots of hidden states which hampers its real-time capability on a small wearable device. Neural network can also be used for phase detection [167], but they face the same issue of inaccuracy during non-periodic motion.

The dynamical approach detects gait phases based on changes in acceleration, or combine with angular velocity [159]. However, these approaches are highly susceptible to changes in walking speed. A slow gait may be mistaken as the end of the swing phase, which also has low angular velocity and acceleration.

Kinematics approach uses tilt sensor [168, 169] to determine the flexion angle of the hip and knees. This is easy to implement, and a simple threshold method may be used to indicate the region of interest. This method is adopted in the current work.

However, several problems still exists and they are discussed in Section 6.1.1.

Chapter 3

Pre-Impact Fall Detection for Generalized Movement

Fall is defined as "*an unexpected event in which the person comes to rest on the ground, floor or lower level*" [2]. Thus, the targeted solution of fall intervention is to prevent the person from having any body part in contact/impact with the ground or lower level after the fall onset. This requires the detection of fall before the impact has occurred, also known as the pre-impact fall detection. Assistance from the fall intervention solution is also only feasible before the impact (foot touchdown is not considered as impact).

Despite all available balance indicators mentioned in Section 2.5, there exists several barriers for not adopting existing stability criteria:

1. lack of accurate individuals joints and bodies parameters
2. lack of muscle state (e.g. fatigue)
3. unpredictable human movements
4. regular walking already consist of falling during the swing phase

These factors create modelling uncertainty that blurs the boundary between stable and unstable gait. Hence, any proposed algorithm must take these uncertainties into account and recreate a boundary for high pre-impact fall detection accuracy. Many factors determine the accuracy of the pre-impact fall detection system: (i) number and position of sensors, (ii) sensor precision and, (iii) sensing algorithm. Sensor precision is not the focus of this research as the precision boils down to the choice of IMUs and filtering algorithm. This chapter focuses on evaluating the number and position of IMUs along with their corresponding sensing algorithm.

Two methods of pre-impact fall detection are proposed. The first is based on AngMom about a pivot point on the subject's body. This method may surpass the other conventional indicators because it accounts for the velocities of all body parts, unlike XCoM. The second method uses HMM as a pre-impact fall detection algorithm. As HMM is a machine learning, data-driven method, it can be customised for every individual without collecting bodily parameters. Humans' unpredictability can also be partially resolved by relying on an extensive database of known motion that are stable. Both methods output an indicative value that can be used to detect falls with a thresholding method. This threshold draws the boundary between fall and non-fall scenarios.

This chapter is organised to first explain the basics of the two proposed algorithms (AngMom, HMM). Then the experimental procedure of data collection and processing is presented. Finally, the performance of both methods is evaluated.

3.1 Angular Momentum

Previously evaluated stability assessment tools were all simplified models that did not take into account the dynamics of the upper body. Considering that the human body is top heavy, with about 68% of human total body mass situated above the hips [170], it is illogical to ignore its movements. The law of physics agrees that bodies of heavier mass affect the entire system more significantly than those of lower mass.

Angular Momentum (AngMom) allows for the inclusion of any body parts during stability assessment, improving the system's accuracy. Regulation of the AngMom is vital to achieve gait stability, usually by swinging the limbs in the opposite direction during gait [171]. When a fall occurs, excessive AngMom gets injected into the system [51], and the body must synchronise its movement to reduce the AngMom to normal levels. The contrast of AngMom between normal motion and falls forms the basis of this proposed fall detection algorithm. No discrepancy has to be made for the algorithm between healthy adults and frequent fallers since it has been noted that there is no significant difference between them [172].

AngMom can be calculated about any point on the body by adjusting the pivot point. Previous studies on walking focused on CoM as the pivot point [51, 171], but shifting the pivot point to the ankle has the advantage of increasing the AngMom contribution of trunk dynamics. Trunk dynamics have shown to be a significant contributor to fall recovery efficiency [20]. Therefore, both CoM and ankle pivot points will be evaluated for their fall detection accuracies.

3.1.1 AngMom About CoM

Whole body AngMom ($\mathbf{H}$) is commonly calculated about the subject's CoM:

$$\mathbf{H} = \sum_{i=1}^n \mathbf{p}^i \times m^i \dot{\mathbf{p}}^i + I^i \omega^i \quad (3.1)$$

where $\mathbf{p}^i$ and $\dot{\mathbf{p}}^i$ are the CoM position and velocity vectors of the i^{th} body with reference to whole body CoM respectively; m^i is the i^{th} body mass; I^i is the global rotational inertia tensor and ω^i is the angular velocity vector with the rotation order YXZ. X is pointing right, Y is pointing up and Z is pointing back.

The global rotational inertia tensor (I^i) is found using:

$$I^i = R^i I_{local}^i R^{iT} \quad (3.2)$$

R^i is the 3×3 rotation matrix of the i^{th} body, and I_{local}^i is the local rotational inertia tensor.

Whole body CoM is calculated as described in Section 2.4.1. The distribution of weight and body dimensions follows the paper from Winter [170].

3.1.2 AngMom about the Ankle

It is proposed that AngMom can be calculated about the ankle to amplify the torso's contribution to overall AngMom caused during falling. This amplification is possible because the torso's moment arm is increased as the pivot point changes to ankle, leading to larger torso AngMom. Conversely, the AngMom of the lower limbs decreases because their moment arm is reduced when a pivot is shifted to the ankle. Torso dynamics is chosen to be amplified because it is a vital factor during fall [20], and it remains relatively stable during normal walking [171].

Similar to the calculation of AngMom about the CoM, AngMom about the ankle uses Equation 3.3 for their calculation.

$$\mathbf{H}_{ank} = \sum_{i=1}^n \mathbf{p}_{ank}^i \times m^i \dot{\mathbf{p}}_{ank}^i + I^i \omega^i \quad (3.3)$$

where $\mathbf{p}_{ank}^i$ and $\dot{\mathbf{p}}_{ank}^i$ are the CoM position and velocity vectors of the i^{th} body with reference to ankle, and $\mathbf{H}_{ank}$ is the angular momentum calculated about the ankle. This equation is very similar to Equation 3.1, except the position and velocity vectors are now referenced from the left or right ankle.

The differences between using different pivots are shown in Figure 3.1. It can be seen that the right ankle and left ankle AngMom are of similar magnitude but in opposite signs and out of phase with each other by half a gait cycle for the x and y-axes. However, the z-axis shows that AngMom about the left and right ankle are of the same magnitude and in phase with each other. This is because z-axis represents the body's rotation about the vertical axis, and pivoting about the left or right ankle should not create any difference. On the other hand, AngMom about CoM has much smaller magnitude as compared to the ankle pivots. This lower magnitude is attributed to segment to segment AngMom cancellation for the left and right limbs when calculating about the CoM.

Figure 3.1: Comparison of filtered walking AngMom calculated about right ankle (red, solid), left ankle (green, dashed), and CoM (blue, dotted).

3.2 Hidden Markov Model as Pre-Impact Fall detector

Since normal walking already consists of falling, it is hypothesised that a machine learning method such as HMM may be better positioned to differentiate ADLs from

falls. Furthermore, other balance indicators (Section 2.4) do not extend well to arbitrary motion and interactions with external supports, such as railings and walkers. Section 2.5.3 has a short description and review of HMM and its applications.

HMM is chosen among other machine learning methods because it relies on past events to determine the probability of the future; similar to how past motion determine the chances of fall. Additionally, the next action depends only on the present action, and not the past; for example, a subject may choose to perform any action, given the present action of having the left leg brought forward. For an external observer, what sequence of actions that lead the left leg forward is inconsequential, because the subject may choose from an infinite amount of actions and sequences to reach the current state. As a result, human motion is said to satisfy the Markov property necessary for the implementation of HMM. Other machine learning techniques such as a recurrent neural network also fulfil the requirement of this project, but they require a much larger dataset and are potentially harder to train and interpret [173].

Previous applications of HMM relied on multiple trained models to separate the input motion into different types. The output of each separate HMM has to be computed and ranked before a final classification can be made. This is computationally expensive and laborious as each HMM has to be trained using pre-classified data. Therefore, a single HMM is proposed to be used only as an anomaly detector. Rather than sorting each motion like stand to sit, walk and fall into separate categories, all ADLs are gathered and trained under one HMM. Falls that are excluded from the training phase will have a very low output probability using the HMM trained using only ADLs. A threshold can then be used to detect falls among the ADLs. Other advantages of using a single HMM over multiple HMM are stated in Table 3.1.

3.2.1 Gaussian Mixture Model

Multivariate GMM is used to soft cluster the data points into different Probability Density Function (PDF)s or mixtures. Split and Merge Expectation Maximization (SMEM) algorithm is used to determine the optimal number of mixture models per dataset [174, 175]. It starts as a regular Expectation Maximization [176] sequence to optimize the mixtures parameters (mean, covariance, expectations and priors) iteratively. The likelihood function ($L(X|\theta)$) allows for estimating the fitting of dataset with the PDF:

Table 3.1: Advantages and Disadvantages of using a single HMM over multiple HMM

Multiple HMM	Single HMM
Higher accuracy as each model can be computed to indicate that a squat data belongs to a squat model and fall data to fall model	Lower accuracy but superior in speed during both training and execution
Ability to differentiate even normal motion into different types. This is due to the presence of multiple models trained using different model types. The model with the highest output will be defined as the motion type	Cannot classify inputs into different motion types as there is only one model. However, anomaly detection is still possible
Requires fall data for the creation of a specific fall model. Obtaining a large fall dataset is extremely difficult because of safety concerns	Requires only regular motion inputs. Significantly easier to obtain than fall data

$$L(\theta_j|X_n) = f(X_1|\theta_j) \dots f(\mathbf{X}_n|\theta_j) \quad (3.4)$$

$$f(\mathbf{X}_n|\theta_j) = \frac{1}{\sqrt{2\pi_j|\Sigma_j|}} \exp\left(-\frac{1}{2}(\mathbf{X}_n - \mu)^T \Sigma_j^{-1}(\mathbf{X}_n - \mu)\right) \quad (3.5)$$

where $L(\theta_j|X_n)$ is the likelihood function; $X_{1,...,n}$ are the multi-dimensional data points; n is the total number of data points; θ_j is the mixture parameters such as priors (π_j), means (μ_j) and covariance (Σ_j); and j is the total number of mixtures. $f(\mathbf{X}_n|\theta_j)$ is the multivariate PDF. The larger the likelihood function, the better the fitting of the dataset with the PDFs.

Splitting and merging occur after maximization of the mixtures' likelihood function. Splitting uses a *modified local kullback divergence* ($E_{div,j}$) as its determining criteria. The modified splitting criteria is calculated as follows:

$$E_{div,j} = D_{LKD,j} * CV_{max,j} * \pi_j \quad (3.6)$$

where $D_{LKD,j}$ is local kullback divergence [175]; $CV_{max,j}$ is the maximum coeffi-

cient of variation of all axis; π_j is the prior of each mixture; $E_{div,j}$ is a value that indicate the divergence of each mixture. The mixture with the highest divergence will be chosen to be split, to form 2 separate mixtures with smaller divergence. The maximum coefficient of variation ($CV_{max,j}$) is calculated with

$$CV_{max,j} = \max \left\{ \frac{\Sigma_j(i, i)}{\mu_{i,j}} \right\} \quad (3.7)$$

where $\Sigma_j(i, i)$ is the i^{th} diagonal element of covariance matrix from j^{th} mixture, and $\mu_{i,j}$ is the i^{th} axis' mean of j^{th} mixture. This modification allows for the splitting process to prioritise large, sparse and poorly fitted mixtures. Previous splitting criteria used only the local kullback divergence [174], which prioritised small and sparse mixtures before larger and slightly less sparse mixtures. This modification speeds up the training process of GMM.

Merging also uses a modified correlation criteria (E_{corr}):

$$E_{corr} = |U_{corr}| \cdot \left(1 - \frac{|\mu_1 - \mu_2|}{|\mu_1| + |\mu_2|} \right) \quad (3.8)$$

where μ_1 and μ_2 are the means of the 2 mixtures to be merged.

$$U_{corr} = \frac{\mu_1^T \mu_2}{|\mu_1| |\mu_2|} \quad (3.9)$$

This allows 2 mixtures with mean of the same vector direction, but have different magnitude to be excluded from being merged.

Bayesian information criterion (BIC) is typically used to judge the feasibility of the SMEM algorithm [177], but it allows for 2 mixtures to have the same parameters as it will significantly increase the BIC value. Hence, a new criterion, called the Likelihood Correlation Criterion (LCC) is proposed to quantify the split merge feasibility:

$$LCC = \ln(L(\theta_j|X_n)) - E_{corr} - N_m * \ln(N_x) \quad (3.10)$$

Where $L(\theta_j|X_n)$ is the likelihood function; E_{corr} is the sum of modified correlation function for all mixtures combination; N_m is the current number of mixtures; and N_x is the number of data points. LCC penalises similar mixtures while trying to keep the number of mixtures to a minimum. The larger the LCC, the closer the algorithm is to finding the local optimum number of mixtures.

3.2.2 Hidden Markov Model

The trained PDFs from the previous section are used as continuous emissions for the CHMM. A single CHMM is used to model all the different motion types, as explained in Table 3.1. The model parameters (λ) of each CHMM are:

$$\lambda = (A, B, \pi, N_s, N_m) \quad (3.11)$$

where A is the state-transition probability matrix; B is the observation or emission matrix; π is the initial state distribution; N_s is the number of hidden states, and N_m is the number of mixtures from GMM.

The initial probability distribution (π) is defined as:

$$\pi = \{\pi_1 \quad \pi_2 \quad \dots \quad \pi_N\} \quad (3.12)$$

where π_k is the probability of the system at state k at beginning of sequence, and its sum must be equal to 1. The transition matrix (A) is:

$$A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1N} \\ \vdots & \vdots & \vdots & \vdots \\ a_{N1} & a_{N2} & \dots & a_{NN} \end{bmatrix} \quad (3.13)$$

where a_{ij} is the probability of going from state i to state j at any time step, and the sum of going from state k to any other state l must be equal to 1. The emission matrix (B) is:

$$B = \begin{bmatrix} b_{11} & b_{12} & \dots & b_{1M} \\ \vdots & \vdots & \vdots & \vdots \\ b_{N1} & b_{N2} & \dots & b_{NM} \end{bmatrix} \quad (3.14)$$

where b_{j,O_t} is the probability of observation O_t belonging to state S_j . This matrix changes with every different input observation.

Baum-Welch re-estimation algorithm is used to train the CHMM parameters. The number of hidden states (N_s) was found by maximising the BIC returned from Baum-Welch re-estimation. After that, the Viterbi algorithm was used to obtain the probability of the output state sequence. The General Hidden Markov Model Library was used to assist in developing the CHMM algorithm used in this study [178].

Baum-Welch algorithm

Baum-Welch is a type of Expectation-Maximization algorithm, similar to SMEM in GMM. It consists of 2 steps, namely expectation and maximisation.

Expectation: For the Expectation step, the main goal is to calculate the **forward**, **backward**, **state transition** and **state probability** at time t .

Forward probability (α) represents the probability of a partial observation sequence until time t , while having state j at time t .

$$\alpha_j(t) = P(O_1, O_2, \dots, O_t, s_j | \lambda) \quad (3.15)$$

$$\alpha_j(1) = \pi_j b_{j,O_1} \quad (3.16)$$

$$\alpha_j(t+1) = \left(\sum_{i=1}^N \alpha_i(t) a_{ij} \right) b_{j,O_{t+1}} \quad (3.17)$$

where

$$b_{j,O_t} = \sum_{m=1}^M c_{im} N(O_t | \mu_m, \sigma_m) \quad (3.18)$$

and $P(O_1, O_2, \dots, O_t, s_j | \lambda)$ represents the probability of observing all the observations from $O_1, O_2, \dots, O_t$ and the state s_j given a set of HMM parameters (λ).

b_{j,O_t} is the weighted sum of the probability of observation sequence O_t for state s_j as shown in emission matrix (B); μ_m and σ_m are the mean and variance for the m^{th} PDF; $N(O_t | \mu_m, \sigma_m)$ is the normal distribution; c_{im} is the weight of the i^{th} state for the m^{th} PDF; a_{ij} is the probability of going from state i to state j shown in the transition matrix A , and π_j is the initial probability of the initial j state.

Backward probability (β) is the probability of the partial observation sequence from time t to end of time T , given state j at time t .

$$\beta_j(t) = P(O_{t+1}, O_{t+2}, \dots, O_T, s_j | \lambda) \quad (3.19)$$

$$\beta_i(T) = 1 \quad (3.20)$$

$$\beta_i(t+1) = \sum_{j=1}^N (a_{ij} b_{j,O_{t+1}} \beta_j(t)) \quad (3.21)$$

where a_{ij} is the probability of going from state i to state j shown in the transition matrix A ; b_{j,O_t} is the weighted sum of the probability of observation sequence O_t

for state s_j shown in emission matrix (B) and Equation 3.18.

State transition probability ($\zeta_{ij}(t)$) is the probability of being in state s_i at time t and in state s_j at time $t + 1$.

$$\zeta_{ij}(t) = P(q_t = s_i, q_{t+1} = s_j | O, \lambda) \quad (3.22)$$

$$\zeta_{ij}(t) = \frac{\alpha_i(t) a_{ij} b_{j, O_{t+1}} \beta_j(t+1)}{P(O | \lambda)} \quad (3.23)$$

$$\zeta_{ij}(t) = \frac{\alpha_i(t) a_{ij} b_{j, O_{t+1}} \beta_j(t+1)}{\sum_{i=1}^N \sum_{j=1}^N (\alpha_i(t) a_{ij} b_{j, O_{t+1}} \beta_j(t+1))} \quad (3.24)$$

State probability ($\gamma_i(t)$) is the probability of being in state s_i at time t .

$$\gamma_i(t) = \frac{P(O_1, \dots, O_t, q_t = s_i | \lambda) P(O_{t+1}, \dots, O_T, q_t = s_i | \lambda)}{P(O_1, \dots, O_T | \lambda)} \quad (3.25)$$

$$\gamma_i(t) = \frac{\alpha_i(t) \beta_i(t)}{\sum_{j=1}^N \alpha_j(t) \beta_j(t)} \quad (3.26)$$

$$\gamma_i(t) = \sum_{j=1}^N \zeta_{ij}(t) \quad (3.27)$$

Maximization: During maximisation, the different HMM parameters are updated to the latest value using the intermediate variables from expectations steps as follows:

The initial state probability (π_j) is updated as:

$$\pi_j = \alpha_j(1) \quad (3.28)$$

State transition probability (a_{ij}) is updated as:

$$a_{ij} = \frac{\sum_{t=1}^{T-1} \zeta_{ij}(t)}{\sum_{t=1}^{T-1} \alpha_i(t)} \quad (3.29)$$

Mixture weightage (c_{im}) is updated as:

$$C_{im} = \frac{\sum_{t=1}^T \gamma_{im}(t)}{\sum_{t=1}^T \sum_{m=1}^M \gamma_{im}(t)} \quad (3.30)$$

Mixture mean (μ_{im}) is updated as:

$$\mu_{im} = \frac{\sum_{t=1}^T \gamma_{im}(t) O_t}{\sum_{t=1}^T \gamma_{im}(t)} \quad (3.31)$$

Mixture Covariance Matrix (Σ_{covim}) is updated as:

$$\Sigma_{covim} = \frac{\sum_{t=1}^T (\gamma_{im}(t) (O_t - \mu_{im})(O_t - \mu_{im})^T)}{\sum_{t=1}^T \gamma_{im}(t)} \quad (3.32)$$

Viterbi algorithm

The Viterbi algorithm finds a path (δ_j) of the highest probability that best accounts for the observations of length t . It is similar to the forward probability variable (α) in the Baum-Welch algorithm, but the state with maximum probability is used instead of summing all the transition probability.

$$\delta_j(t) = \max_{q_1, \dots, q_{t-1}} P(q_1, \dots, q_t = s_j, O_1, \dots, O_t | \lambda) \quad (3.33)$$

$$\delta_j(1) = \max(\pi_i b_{i,O_1}) \quad 1 \leq i \leq N_s \quad (3.34)$$

$$\delta_j(t+1) = (\max_i (\delta_i(t) a_{ij})) b_{j,O_t} \quad 1 \leq i \leq N_s, 1 \leq t \leq T-1 \quad (3.35)$$

3.2.3 Feature Extraction

Although most of the reviewed HMM algorithms (Section 2.5.3) use some form of feature extraction to extract features from their data before supplying it as input, none of them was used in this project except for the heading constraint (Section 3.4.1). This is because the final algorithm has to be implemented in real time, and most feature extraction methods will increase the processing time while also increasing the input vector size of the HMM.

3.3 Experimental Setup

3.3.1 IMU placement

IMU is chosen as the sensor of choice because of its size, lightweight, and the ability to be used in multiple environments (see Section 2.5.1). Apart from the sensor choice, the number of sensors and its placement is also a critical choice to consider.

Fall detection systems typically use a single sensor that is placed on the least obstructive position to increase user's acceptance. However, the number of IMUs and its position affect the detection algorithm significantly. For example, wrist placement triggers many false alarms as the hands are constantly moving and hitting on to hard surfaces [179]. Hip placement is normally cited as uncomfortable and will not be useful during the critical phase of getting up from the bed as users normally do not sleep with the sensors around their waist [180].

The most logical choice of sensor location is to place them at body parts that contribute the most to balance while eliminating sensors at lower contributing bodies to increase user acceptance. Heavier body parts such as shanks, thighs and torso makeup approximately 70% of the total body weight and thus contribute significantly to the stability of the whole body CoM [20]. Lighter body parts such as the arms and forearms contribute lesser, but they are essential during dynamical control as they have a higher moment of inertia and often have movements of high velocity. Since the target audience are the elderly who are slower in their movements and do not engage in highly dynamical movements, the dynamics of their upper limbs do not affect their balance significantly. As such, it is logical for the IMUs to be located at the chest, thighs and shanks (Figure 3.2). For this study, the inclusion of multiple sensors is not a big drawback as the envisioned exosuit should surround the user.

3.3.2 Data Collection

Kinematic data were collected according to protocols approved by Nanyang Technological University (NTU) Institutional Review Board (IRB) (IRB-2017-04-014-01, 3 subjects) and Shenzhen University (SZU) IRB (20190012, 15 subjects). A total of 18 subjects were recruited for this experiment. They were 7 females and 11 males with an average age of 23 ± 0.9 years, average height of 165 ± 7.97 cm, average weight of 57.22 ± 10.0 kg, and an average Body Mass Index (BMI) of 21.17 ± 2.28 . All of them has no history of locomotor impairment, neurological impairment or cardiovascular diseases.

Ten kinds of motion were recorded to represent the majority of balancing tasks necessary during different activities of daily living. They were:

1. Standing still
2. Walking at normal speed along an L-shaped pathway
3. Walking backwards

4. Walking sideways (left and right)
5. Bending forward and pick up an object on the floor at half-arm length with locked knees
6. Bending forward and pick up an object on the floor at half-arm length with slightly bent knees
7. Bending forward and pick up an object on the floor at half-arm length with fully bent knees
8. Reaching out for object at waist height, placed at one arm length
9. Reaching out for object at shoulder height, placed at one arm length
10. Reaching out for object at head level, placed at one arm length

These ten motion were chosen as they represent the majority of movements required for ADLs, such as basic mobility, bathing, grooming, dressing and feeding. They do not include activities that require interaction with external objects or the environment (e.g. railings, bed or a walker), as the current focus is only on the unassisted upright motion. Walking was done at a self-selected speed, and the subjects were asked to change his heading direction in the order of left 90 deg, right 180 deg, right 90 deg and left 180 deg. The reaching and bending actions were used to simulate highly imbalance position. A total of 2 trials were collected per subject, and each trial consisted of a single run of the walking motion, with 3 repeated trials of the bending and reaching motion. Additionally, the 15 subjects recruited under SZU performed 8 more tasks:

1. Walking at slow speed along an L-shaped pathway
2. Walking at fast speed along an L-shaped pathway
3. Reaching forward for an object at waist height placed medially at a distance half of the subject's height
4. Reaching forward for an object at shoulder height, placed medially at a distance half of the subject's height
5. Reaching forward for an object at head level, placed medially at a distance half of the subject's height

6. Reaching sideways for an object at waist height, placed medially at a distance half of the subject's height
7. Reaching sideways for an object at shoulder height, placed medially at a distance half of the subject's height
8. Reaching sideways for an object at head level, placed medially at a distance half of the subject's height

These tasks extended the variability of the ADLs collected under the initial 10 motion. These additional motion were included in the training dataset used during HMM training.

The trip is the only induced fall in the whole of this project. Tripping is induced via 2 methods: (1) Rope pull by investigators or (2) with FIMP. The 3 subjects recruited under NTU had their trips induced via a tug on a rope tied around their ankle by investigators. The remaining 15 subjects recruited under SZU had their trips induced by FIMP (see Chapter 6). The first 3 subjects were preliminary trials which later inspired the creation of FIMP to solve the problems of inconsistent tripping.

Nonetheless, both tripping methods trip the subjects during the mid-swing and late swing phase to induce the elevating and lowering recovery strategy respectively. After the trips, subjects were asked to recover as they wish, and they were to stand still after a successful recovery. Every subject has to undergo a minimum of 6 random trips, whereby a minimum of 3 is for mid swing trip and 3 for late swing trip. Subjects were asked to wear a slack safety harness attached to either a manually movable platform or an automated moving platform for the rope pull by investigator trials or FIMP trials respectively.

Measurement Method

Data was collected using 3-SpaceTM USB/RS232 IMUs obtained from *Yost Labs* (see Appendix G.1). Acceleration, angular velocity and filtered quaternion output were streamed from the IMU at a maximum sampling rate of 850Hz using their proprietary Q-COMP filter. In reality, an average of 330Hz sampling rate was obtained. The IMUs were connected to a SBC (Raspberry Pi 3b+) using a 7-port USB hub, with power supplied to the SBC using a 5V/2.1A power bank. Data were processed in real time and were also stored in a binary file for recording purposes. Streaming, data processing and fall detection algorithms were written in C++ using USB serial communication libraries and Eigen matrix library [181] for matrix operations.

All subjects had 5 IMUs strapped onto their shank, thigh and torso as shown in Figure 3.2. The IMUs were placed at the front of chest (sternum), left and right thigh (5cm above knee cap) and left and right shank (5cm above medial malleolus located at the bottom of tibia bone). The IMUs on the lower limbs are to be aligned with the line formed by joining the iliac crest to the patella and also the patella to the middle of the ankle (demarcated by the midpoint between the 2 malleoli of the tibia).

Figure 3.2: (a) IMUs body placement on torso, thighs and shanks (circled in red); (b) The backpack (red) housed the SBC, USB-hub and powerbank.

IMUs on the chest were placed with its USB port facing the ground while the rest have their USB port facing upwards. This orientation was chosen to facilitate cable routing; hence, the different initial axis of the IMU must be taken into account for further processing.

3.3.3 Pose Initialization

A simple 5 joints, 6 body parts, stickman model, was used for subject modelling. The body parts are the torso, pelvis, thighs and shanks. The joints are the lumbosacral

joint, 2 hip joints and 2 knee joints. Global origin was set at the middle of the lumbosacral joint. The distribution of weight and body dimensions was with reference from the paper from Winter [170] while the coordinate system was in accordance to the OpenGL convention with X pointing to the right, Y straight up and Z to the back (towards the viewer).

Figure 3.3: Basic stickman model used to model the subjects. A back view of the model in initialisation pose. The red boxes represent the IMUs, and the only joints in the stickman are lumbosacral joint, hip joints and knee joints. $+X$ axis pointing to the right, $+Y$ axis points straight up, and $+Z$ axis points to the back (towards the viewer)

The initialisation pose was set to be an upright standing posture with the back and heels straight and knees locked. Although the hands were not tracked, they still affected the body posture. Hence, the hands were kept at the side of the body. Initial IMUs orientation was obtained when the user pressed a button after assuming the initial static pose. This initial orientation was inverted (conjugated) and multiplied with subsequent IMUs orientation to ensure that all data were referenced from the initial pose.

$$Q^i = \overline{Q_{init}^i} * Q_{raw}^i \quad (3.36)$$

where Q_{raw}^i is the i^{th} body raw quaternion obtained from the IMU; $\overline{Q_{init}^i}$ is the i^{th} body raw conjugate quaternion at initial pose; Q^i is the quaternion from the initial pose and $*$ is the Hamilton product.

3.4 Data Processing

3.4.1 Heading Angle Constraint

Majority of human motion occur in the sagittal plane, but as the heading angle changes, the IMU axis does not automatically realign with the new sagittal plane of the human. This misalignment causes difficulty during kinematics study as each plane of movement cannot be individually analysed. Hence, it is important to make the coordinate system of the IMUs align themselves with the human reference frame such that sagittal plane movements always occur in the same IMU plane.

The solution is to extract the heading angle and use it to transform all motion to align with a single Coordinate System (CS). The torso's heading angle is used as the overall heading angle instead of the lower limbs because its smooth trajectory allows for smooth heading angle transition. Heading angle obtained from the lower limbs are subjected to much higher noise, and the left and right lower limbs adopt different heading angle when the body is turning.

Heading angle (ψ) is extracted from the torso by converting the torso quaternion into Euler angles with YXZ rotation order. Assuming that all activities were performed in an upright position and Y-axis remained as the vertical axis, the desired heading angle can be calculated as the rotation about Y-axis. Calculation of the remaining Euler angles, the rationale for choosing YXZ rotation, and handling of singularities are stated in Appendix A.

$$\psi = \text{atan2}((2 * q_x * q_z + 2 * q_w * q_y), (q_w^2 - q_x^2 - q_y^2 + q_z^2)) \quad (3.37)$$

where ψ is the heading angle, and q_w, q_x, q_y and q_z are the values of each quaternion component. This heading angle is then used to reorient all the IMU data such that the model will predominantly face the global frontal plane. To do so, a quaternion is formed from the heading angle:

$$\begin{aligned} Q_\psi &= a.1 + bi + cj + dk \\ a &= \cos(-\psi/2), \\ b &= 0 \\ c &= \sin(-\psi/2) \\ d &= 0 \end{aligned}$$

The value of ψ is negative to cancel all rotation about the yaw axis and Q_ψ is the

inverse heading quaternion. This inverse heading quaternion will then be multiplied with the body orientation obtained in Equation 3.36 as stated below:

$$Q_{ro}^i = Q_\psi * Q^i \quad (3.38)$$

where Q^i is the i^{th} body quaternion obtained in Equation 3.36, and Q_{ro}^i is the inverse heading quaternion obtained from above.

As a result, the horizontal line representing the pelvis, as shown in Figure 3.3 will not rotate along the vertical axis, as all Y-axis rotations are cancelled.

3.4.2 Acceleration and Angular velocity Reorientation

The acceleration and gyroscope data are not subjected to the same heading angle reorientation operation as they are derivative of position and orientation. They are always referenced to the local CS, unlike the orientation calculation, which is referenced to the global frame. Instead, the acceleration and gyroscope data are reoriented using the heading constrained reoriented quaternion (Q_{ro}^i , see Equation 3.39).

$$Q_{acc}^i = Q_{ro}^i * Q_{rawacc}^i * \overline{Q_{ro}^i} \quad (3.39)$$

where Q_{rawacc}^i and Q_{acc}^i are raw and reoriented acceleration vectors expressed as quaternions respectively (w component of quaternion is set as zero). The same is done with the raw gyroscope data.

3.4.3 Velocity estimation from IMUs

Before evaluation of exosuit performance, linear body velocity needs to be calculated as it is a critical factor used in many balance indicators. However, IMUs that are used in this experiment are known to face the error accumulation problems. Fortunately, it is possible to use the stride length of normal walking gait to determine the walking speed [182].

Firstly, the tangential velocity of the lower limbs is estimated from the angular velocity measured from the gyroscope (Figure 3.4):

$$\mathbf{v}_t = \omega r_{limb} \quad (3.40)$$

where v_t is the tangential velocity; ω is the angular velocity of an axis obtained from

Figure 3.4: Decomposition of the tangential velocity (v_t) obtained from gyroscope (ω) to linear velocity ($\mathbf{v}_{linear}$).

the gyroscope, and r_{limb} is the length of the lower limb that the IMU is placed on. Next, the tangential velocity is decomposed into linear velocity using the direction vector of its corresponding lower limb:

$$Q_{dir} = Q_{ro}^i * Q_{\hat{y}} * \overline{Q_{ro}^i} \quad (3.41)$$

where Q_{ro}^i is the rotation quaternion of the IMU's attached leg (see Section 3.4.1); $Q_{\hat{y}}$ is the unit vertical vector $([0, 0, 1, 0])$ used to represent the initial direction vector of the lower limb, and Q_{dir} is the resultant quaternion of the lower limb. The direction vector ($\mathbf{p}_{dir}$) is obtained from Q_{dir} by removing its w component. The direction vector is then projected to the XY, XZ or YZ plane to form the rotating arm that correspond to each of the angular velocity axis from the gyroscope. A vector is projected onto the YZ plane by removing its X component:

$$\mathbf{p}_{dir,yz} = [0, p_{dir,y}, p_{dir,z}]$$

where $p_{dir,y}$ and $p_{dir,z}$ is the y and z component of the direction vector ($\mathbf{p}_{dir}$), and $\mathbf{p}_{dir,yz}$ is the projected vector.

Finally, the projected vector is rotated 90 deg to form the direction vector that the tangential velocity is acting on. Linear velocity along each axis is calculated by multiplying the tangential velocity with its corresponding projected direction vector. Since there are 3 orthogonal angular velocity from the gyroscope, each of them are decomposed into their linear velocity before summing them to form the

final linear velocity ($\dot{\mathbf{p}}$):

$$\dot{\mathbf{p}} = \mathbf{p}_{dir,yz}(\omega_x \cdot r_{limb}) + \mathbf{p}_{dir,xz}(\omega_y \cdot r_{limb}) + \mathbf{p}_{dir,xy}(\omega_z \cdot r_{limb}) \quad (3.42)$$

The pelvis (estimated CoM) linear velocity is calculated by summing the linear velocity of the stance thigh and shank (Figure 3.5). The stance leg changes with every gait cycle; hence, the source of the pelvis linear velocity will also change at every gait cycle. Individual body linear velocity is then calculated by summing their decomposed linear velocity with the pelvis velocity.

Figure 3.5: An example of the estimated CoM linear velocity of a single trip trial.

Even though the results showed that this method can reliably estimate the linear velocity, it assumes that the stance leg does not slip or skip. When slip or skip occurs, the thigh and shank angles stay relatively constant while moving forward. The gyroscope cannot capture that linear motion as it can only measure angular velocity. Additionally, the effect of the ankle on the pelvis velocity is not accounted. Hence, the estimated velocity in this experiment is underestimated. However, it should be sufficient to measure the relative effect of the balance indicators with and without exosuit assistance.

3.5 AngMom Results

3.5.1 IMU vs Camera Comparison

Walking AngMom about the CoM obtained from the 5 IMUs were first validated against camera-based motion capture data from [171]. The processed data is calculated based on the 5 IMUs with heading angle post-processing. It was further normalised by the weight, height and travelling velocity of the subject, before averaging and filtering 5 gait cycles for comparison (shown in Figure 3.6). A 2nd order Butterworth low pass filter of 6Hz was applied to the AngMom.

The IMU data showed a general trend that agrees with Herr *et al.* [171] camera data. However, some discrepancies exist between the magnitude of all axis. The x-axis AngMom has an offset throughout the entire gait cycle because of the unaccounted foot angular momentum. Herr *et al.* [171] showed that both right and left foot provides significant angular momentum in the same direction for the second principal component, leading to the observed offset. Foot angular momentum was unaccounted because of the lack of sensors mounted on the foot. In the y-axis, angular momentum from IMU oscillated around the camera's angular momentum. This was also due to unaccounted foot flexion that swings medially and laterally during gait. However, it did not create an offset because the magnitude between the left and right feet principal components are mostly equal and in opposite directions, unlike the x-axis. In the z-axis, the magnitude of AngMom was much higher for the IMU. Unlike the other axes, this increased magnitude was caused by the unaccounted arm swinging angular momentum and is also observed by Collins *et al.* [183]. The root mean square error values are 0.0251, 0.0234 and 0.0107 for the x, y and z-axes respectively.

3.5.2 AngMom about CoM as Fall Indicator

Since the AngMom collected from IMUs is similar and validated with those collected from the motion-captured camera, it is now possible to compare fall with the ADLs. The first comparison is made between standard walking data and trip data (Figure 3.7). A significant change occurs about 400ms into the trip, which is shown by the sharp spike in the x-axis. This significance is also observed when comparing trips to other walking motion like backwards and sideways walking. Although there is also significance shown in the z-axis, its magnitude did not differ from the other walking actions as much as the x-axis.

Figure 3.6: Comparison of Normalized AngMom data obtained from [171] (red, solid) and IMU (blue, dashed). The coordinate frame follows Herr *et al.* [171], with the z-axis directed vertically, x-axis pointing to the right and y-axis pointing forward. The

Trips were then compared with other static motion (bending/ squatting/ reaching). Subjects were asked to execute and hold the 6 bending and reaching motion stated in Section 3.3.2 for 3 seconds before recovering. Then, they repeated the same motion with no holding time between bending/reaching and standing upright.

Results shown in Figure 3.8 indicate that the significance of the spike corresponding to the trip decreases when comparing to bending forward motion. Bending motion requires a large movement of the torso, which causes a large increase in AngMom. On the contrary, the reaching motion are only at the waist, shoulder and head height, which does not require much movement. Hence, its generated AngMom remains minimal.

3.5.3 Performance of AngMom about CoM as Fall Indicator

The following factors determine the performance of the algorithm:

1. Sensitivity = $TP / (TP + FN)$
2. Precision = $TP / (TP + FP)$

Figure 3.7: Normalized AngMom comparison between a trip (red), normal forward walking (green, dash), backwards walking (blue, dotted), and sideways walking (yellow, dashdot). The vertical black line represents the start of fall, when the leg has been pulled by the rope. (a) AngMom about the x-axis (right); (b) AngMom about y-axis (vertical); (c) AngMom about z-axis (backwards).

3. Detection Latency = time difference from fall initiation to fall detected

where True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) are true positive (true fall), true negative (true normal motion), false positive (false fall) and false negative (false normal motion) respectively. Although specificity is often cited as one of the indicators to evaluate a model's accuracy, it is unsuitable in this experiment because of the significantly large number of negative trials as compared to positive trials. This imbalance causes result skewing, which may lead to misinterpretation of results [184]. Nonetheless, the ROC curves which compares the sensitivity and specificity is shown in Appendix B. Here, PR curves are used instead of ROC curves. PR curves plot precision (y-axis) against sensitivity (x-axis). A model with a perfect classification algorithm will be depicted as a point at the [1.0, 1.0] position. A good model will have a curve that bows towards the [1.0, 1.0] point. On the contrary, a model that fails at classification will have a flat line on the x-axis.

The AngMom threshold used for distinguishing falls from ADLs can be adjusted

Figure 3.8: AngMom comparison between trips (red, solid) and bending/reaching motion (green, dash). The different number above each green spikes indicate the type of motion: (1) bend forward with straight knees, (2) bend forward with bent knees, (3) full squat, (4) reaching at waist height, (5) reaching at shoulder height, and (6) reaching at head height. The black vertical lines indicate trip initiation.

to alter the sensitivity, precision and detection latency of the algorithm. Increasing the threshold will improve sensitivity, but increases detection latency and decreases precision. The opposite holds when decreasing the threshold value. The changing sensitivity and precision values are plotted as PR curves shown in 3.9.

The PR curve indicates that AngMom calculated about the CoM is not a good fall detector as it is far away from a horizontal line at a precision of 1. Furthermore, it only has an AUC of 0.3, which is worse than a random classifier whose AUC will be 0.5.

A sensitivity of 4.8% and precision of 95% is found when using AngMom calculated about the CoM as a fall detection algorithm. It has an average detection latency of 153.8ms.

Figure 3.9: The PR curves (solid red) showing the accuracy of AngMom about the CoM as a fall detection algorithm. The red shaded cloud represents maximum and minimum precision at every TPR samples. The red dotted line shows the standard deviation of precision at their corresponding TPR.

3.5.4 AngMom about Ankle as Fall indicator

Figures 3.10 to 3.13 show the AngMom of the left and right ankle when comparing between different walking directions and also bending and reaching motion. The overall magnitude of AngMom decreases and the significance of the peak associated with the trip instance is also diminished for the ankle pivot points, relative to the CoM pivot. This suggests that even though the torso's contribution to AngMom may be larger, the thigh's momentum when calculated about the ankle is also larger. Coupled with the thigh's larger and faster motion, the significance of the torso decreases in overall significance when compared to the CoM pivot point.

3.5.5 Performance of AngMom about Ankle as Fall indicator

The PR curves for the left and right ankle as a pivot point for AngMom calculation are shown in Figures 3.14 and 3.15, for the right and left ankle respectively. Both left and right pivots attained an AUC of 0.03, which is similar to the CoM pivot point.

The best performing threshold of the right ankle pivot point gives a sensitivity of 4.76%, precision of 94.99% and a detection latency of 153.5ms. Likewise, a sensitivity of 4.57%, precision of 98.2% and a detection latency of 73.9ms are obtained for the left ankle. This AUC and precision information indicates that AngMom calculated about the ankle pivots is unsuitable for a fall detector, as it cannot even

Figure 3.10: Normalized AngMom about the right ankle compared between a trip (red), normal forward walking (green, dash), backwards walking (blue, dotted), and sideways walking (yellow, dash-dot). The vertical black line represents the start of fall, when the leg has been pulled by the rope. (a) AngMom about the x-axis (right); (b) AngMom about y-axis (vertical); (c) AngMom about z-axis (backwards).

surpass the performance of a random classifier.

3.5.6 Discussion

AngMom was originally proposed as a fall detection algorithm because AngMom was shown to be controlled and regulated during normal walking [171]. However, when comparing it to other ADLs, the deviation magnitudes of the AngMom during unregulated trips is insufficient to be used as an accurate fall detector. The performance of AngMom calculated about any of the proposed pivot points (CoM, left and right ankle), did not exceed that of even a random classifier. Hence, AngMom will be dropped as a viable fall identification algorithm.

Figure 3.11: Normalized AngMom about the left ankle compared between a trip (red), normal forward walking (green, dash), backwards walking (blue, dotted), and sideways walking (yellow, dashdot). The vertical black line represents the start of fall, when the leg has been pulled by the rope. (a) AngMom about the x-axis (right); (b) AngMom about y-axis (vertical); (c) AngMom about z-axis (backwards).

Figure 3.12: AngMom comparison between trips (red, solid) and bending/reaching motion (green, dash). The different number above each green spikes indicate the type of motion: (1) bend forward with straight knees, (2) bend forward with bent knees, (3) full squat, (4) reaching at waist height, (5) reaching at shoulder height, and (6) reaching at head height. The black vertical lines indicate trip initiation.

Figure 3.13: AngMom comparison between trips (red, solid) and bending/reaching motion (green, dash). The different number above each green spikes indicate the type of motion: (1) bend forward with straight knees, (2) bend forward with bent knees, (3) full squat, (4) reaching at waist height, (5) reaching at shoulder height, and (6) reaching at head height. The black vertical lines indicate trip initiation.

Figure 3.14: The PR curves (solid red) showing the accuracy of AngMom about the right ankle as a fall detection algorithm. The red shaded cloud represents maximum and minimum precision at every TPR samples. The red dotted line shows the standard deviation of precision at their corresponding TPR.

Figure 3.15: The PR curves (solid red) showing the accuracy of AngMom about the left ankle as a fall detection algorithm. The red shaded cloud represents maximum and minimum precision at every TPR samples. The red dotted line shows the standard deviation of precision at their corresponding TPR.

3.6 HMM Results

Post-processed data from the 5 IMUs were separated into the datasets as shown in Table 3.2. These datasets were chosen as they represent all of the raw data used for feature extraction in previous CHMM studies [110–113, 185]. Euler angles with rotation order YXZ are used to obtain the roll(z), pitch(x) and yaw(y) values after the sagittal plane reorientation. Direction vector is also used as input for one of the dataset. It is calculated by multiplying a vertical vector ($[x,y,z] = [0,1,0]$) with reoriented quaternion (Q_{ro}^i). Direction vectors allow for the elimination of wrap angles entirely, ensuring continuous analogue input into the HMM without discrete jumps.

Feature extraction was not considered for modifying the dataset as simple features like mean, standard deviation and normalised acceleration alone do not encode enough information to identify a pre-impact fall, while complex features like FFT (Fast Fourier transform) and LPC (Linear Predictive Coding) increase the input dimensions significantly, and hence computational complexity. For each of the dataset, the CHMM algorithm was run with a sliding window of 4 samples (12 ms), and stride of 1 sample.

3.6.1 Comparing datasets using Fall motion

Although trips and its recovery motion can be described as a more elaborate walking pattern [49], its velocity profile varies significantly from normal motion. CHMM can detect these differences and outputs a value that represents the probability of observing that motion. An example of the CHMM output, based on the 6th dataset, is shown in Figure 3.16. It can be observed that when falls occur, a negative spike will occur (7 falls in total).

3.6.2 Selecting the best Dataset

The following indicators are used to determine performance of datasets:

1. Sensitivity (TPR) = $TP / (TP + FN)$
2. Precision = $TP / (TP + FP)$
3. Detection Latency = time difference from fall initiation to fall detected

These indicators are the same used to evaluate AngMom in Section 3.5.3.

Table 3.2: Setup of different dataset

Dataset	IMU in use	Sensors in use	Axes
1	Torso	Acc, Gyro	6
2	Torso	Acc, Gyro, R, P	8
3	Torso	Acc, Gyro, R, P, Y	9
4	Torso	Acc, Gyro, Direc	9
5	Torso	Acc, Gyro, Quat	10
6	Torso, Thigh	Acc, Gyro	18
7	Torso, Thigh	Acc, Gyro, R, P	24
8	Torso, Thigh	Acc, Gyro, R, P, Y	27
9	Torso, Thigh	Acc, Gyro, Direc	27
10	Torso, Thigh	Acc, Gyro, Quat	30
11	Torso, Thigh, Shank	Acc, Gyro	30
12	Torso, Thigh, Shank	Acc, Gyro, R, P	40
13	Torso, Thigh, Shank	Acc, Gyro, R, P, Y	45
14	Torso, Thigh, Shank	Acc, Gyro, Direc	45
15	Torso, Thigh, Shank	Acc, Gyro, Quat	50

2nd column states the IMUs placement, 3rd column sensor data in used, and 4th column states the number of sensor axis. R = Roll, P = Pitch, Y = Yaw, Direc = Direction vector.

Figure 3.16: HMM probabilities of fall trials with multiple perturbations (blue) versus ADLs trials with walking, reaching and bending tasks (trial 1 (green), trial 2 (red)). Each blue spike in the fall trial correspond to a fall.

The sensitivity, precision and detection latency of the HMM can be altered by adjusting the threshold value used to discriminate between falls and ADLs. Increasing the threshold will improve sensitivity, but increases detection latency and decreases precision. The opposite holds when decreasing the threshold value. The changing sensitivity and precision values are plotted as PR curves shown in 3.17.

Dataset 6, which uses accelerometer and gyroscope data from IMUs mounted on the torso and both thighs, shows the highest AUC. AUC allows for the selection of the best model, and an AUC of 1.0 indicates a perfect model that detect all falls without false alarm.

Based on the highest combined sensitivity and precision, dataset 6 is still identified as the most suitable pre-impact fall detector. Furthermore, dataset 6 has the highest sensitivity and precision at 90.4% and 87.4%. The performance of the remaining dataset is shown in Table 3.3. The corresponding detection latency of the dataset 6 is $128.21ms$, which is within the $500ms$ time duration of a trip. Even though dataset 13 has excellent latency and sensitivity, it is not selected for the most suitable dataset because of its low precision. Furthermore, dataset 11 to 15 requires input from 5 IMUs, which increases the computational load of the SBC. Since the IMU samples at $333Hz$, the computation latency of the dataset must be lower than $3ms$. Dataset 6 can achieve a computation latency of $0.85ms$ using OpenMP multithreading technology [186] on Raspberry Pi 3B+. Since dataset 6 requires less than 30% of the IMU's sampling interval to complete, it is suitable for actual system implementation. It is also interesting to note that all datasets with quaternion as an input performed badly. This is likely due to the discrete jumps that might occur in quaternion during rotations.

The PR curves of the rest of the subjects are shown in Appendix

3.6.3 Effect of Sliding Window Size

The results above are based on a sliding window of size 4 with a stride of 1 (about 12ms). To understand the effect of sliding window size, the size is changed to 30 (about 120ms of real-world time) and 200 (about 800ms). The results are shown in Table 3.5. Only the 3 subjects recruited from NTU were included in this sliding window effect study.

Comparison with Table 3.4 shows that a larger window size does not equate to higher sensitivity and precision. However, the best performing dataset for a window size of 30 is still dataset 6 with torso and thighs acceleration, gyroscope data at 89%

PR Curves for all HMM datasets with 4 sliding window

Figure 3.17: Precision Recall curves of all 15 datasets. Each PR curve shows a solid line representing the precision magnitude at every sensitivity value. The red shaded cloud represents maximum and minimum precision at every TPR samples. The red dashed line shows the standard deviation of precision at their corresponding TPR. AG = Accelerometer and Gyroscope; AGO2 = Accelerometer, Gyroscope, Yaw and Pitch; AGO3 = Accelerometer, Gyroscope, Roll, Yaw and Pitch; AGD = Accelerometer, Gyroscope and 3 axis direction vector; AGQ = Accelerometer, Gyroscope and Quaternion.

Table 3.3: Performance of datasets with window size of 4 and 18 subjects

Dataset	Sensitivity	Precision	Latency[ms]
1	0.821	0.890	55.08
2	0.784	0.878	74.50
3	0.793	0.864	95.07
4	0.771	0.862	110.01
5	0.759	0.888	114.87
6	0.904	0.874	128.21
7	0.849	0.888	136.63
8	0.845	0.888	145.82
9	0.841	0.890	154.87
10	0.814	0.888	163.83
11	0.881	0.894	170.65
12	0.891	0.834	55.51
13	0.913	0.818	54.57
14	0.816	0.890	54.73
15	0.817	0.818	58.13

Table 3.4: Performance of datasets with window size of 4

Dataset	Sensitivity	Precision	Latency[ms]
1	0.74	0.93	200.13
2	0.92	0.84	159.08
3	0.92	0.82	178.39
4	0.93	0.74	165.87
5	0.80	0.90	263.16
6	0.93	0.94	191.49
7	0.94	0.85	204.05
8	0.90	0.85	217.20
9	0.89	0.81	200.94
10	0.71	0.69	151.57
11	0.84	0.94	194.89
12	0.87	0.86	148.06
13	0.87	0.81	158.06
14	0.89	0.81	200.94
15	0.65	0.52	110.87

Table 3.5: Performance of datasets with window size of 30

Dataset	Sensitivity	Precision	Latency[ms]
1	0.81	0.83	202.86
2	0.94	0.83	164.48
3	0.86	0.82	163.95
4	0.89	0.81	180.66
5	0.85	0.68	263.67
6	0.89	0.84	146
7	0.92	0.85	147.03
8	0.87	0.82	164.96
9	0.94	0.75	167.58
10	0.65	0.48	197.55
11	0.8	0.68	196.33
12	0.81	0.72	253.98
13	0.76	0.67	201.26
14	0.94	0.75	167.58
15	0.49	0.34	109.55

Table 3.6: Performance of datasets with window size of 200

Dataset	Sensitivity	Precision	Latency[ms]
1	0.96	0.81	303.21
2	0.93	0.86	315.29
3	0.89	0.83	396.83
4	0.96	0.80	362.66
5	0.80	0.57	357.81
6	0.75	67.09	384.50
7	0.63	0.53	661.38
8	0.34	0.35	740.75
9	0.38	0.61	875.89
10	0.25	0.27	2925.68
11	0.30	0.56	984.00
12	0.30	0.46	1135.39
13	0.30	0.50	1121.01
14	0.38	0.61	875.89
15	0.33	0.36	1173.86

sensitivity and 84% precision. The best dataset for 200 window size is dataset 1 with torso acceleration and gyroscope data, and it has 96% sensitivity and 81% precision.

The change of best dataset from dataset 6 when using a small window size to dataset 1 using a larger window size may be attributed to the lesser influence of noise on output probability with larger window size. However, the larger window size meant that more samples have to be collected before a fall can be detected, i.e. longer detection latency.

As the window size increases slightly from 4 to 30, the detection latency did not change significantly. However, when the window size increases to 200, the detection latency increases by about 100ms for the best dataset. As such, the conclusion can be made to decrease the window size to as small as possible but still maintaining high sensitivity and precision.

3.6.4 Inter-subject HMM Compatibility

Inter-subject HMM compatibility allows for one subject's trained HMM to be used on another subject. This is useful in reducing the training time or even eliminating training. Inter-subject compatibility is tested with only the 3 subjects recruited under NTU. A sliding window of 4 and dataset 6 (accelerometer and gyroscope data from the torso and 2 thighs) was used. The inter-subject HMM performance is shown in Table 3.7

Table 3.7: Inter-Subject HMM Compatibility

	Personalized HMM		Inter Subject 1		Inter Subject 2	
	Sensitivity	Precision	Sensitivity	Precision	Sensitivity	Precision
Subject 1	1.00	1.00	0.79	0.51	0.75	0.56
Subject 2	1.00	1.00	0.95	0.78	0.75	0.56
Subject 3	0.79	0.82	0.64	0.61	0.43	0.48

None of the results from inter-subject testing outperforms the accuracy obtained from a personalised HMM. Hence, it is not advisable to use HMM of another subject. However, training may converge faster if another subject's HMM is used as an initial condition.

3.6.5 Discussion

The results show that HMM can reliably distinguish pre-impact fall scenarios from walking motion, with a detection latency of around 130ms with a window size of 4

at 333Hz. However, more tests must be conducted to determine if the algorithm can identify true fall from motion that have interaction with the environment.

In addition, inter-subject compatibility is high, even though new HMM training is supposed to be conducted for each new subject. This saves on post-processing time and potentially mean that newer users do not need to perform the basic 10 motion first before the fall detection algorithm can perform. However, its accuracy is not as good as an individualised HMM.

Additional advantages/disadvantages of using HMM over other analytical tools as mentioned in Section 2.5 are listed below:

HMM Advantages:

- Output can be generalised to a larger group of subjects with more data
- Inconsistency in data will be removed with the presence of large datasets required by machine learning algorithms.
- Multiple scenarios can be handled with no hardcoding necessary

Disadvantages:

- A large database is needed
- A final threshold selection is still needed for decision making

3.7 Chapter Conclusion

The first component of an exosuit for fall intervention is the fall detection system. Here, a fall detection system based on IMUs mounted on the torso, thighs and shanks is presented. Post-processing of the data was discussed, with emphasis on constraining the heading angle of the subject to the global sagittal plane for better detection accuracy. Two algorithms for detecting falls using the IMUs output were discussed. The first was based on angular momentum, which is regulated during normal walking. However, its performance as a fall detection algorithm underperformed even the random classifier. Hence, the AngMom is dropped as a viable fall indicator.

The second algorithm uses Hidden Markov Model to detect falls as anomalies. ADLs were used as inputs to train a single model of HMM. This creates a HMM which outputs a high probability when ADLs was in process, while trips will have a low probability output. A threshold value is then used to distinguish fall from

ADLs. Results showed that HMM can reliably distinguish pre-impact fall scenarios from walking motion, with a sensitivity of 90.4%, precision of 87.4% and a detection latency of around $130ms$ with a sliding window size of 4 at 333Hz. However, more tests must be conducted to determine if the algorithm can identify true fall from motion that have interaction with the environment.

3.8 Future Work

The algorithm can be further improved by tuning the CHMM parameters such as training window, threshold and Markov model architecture. Further studies must also be conducted on the performance of pre-impact fall detection when interacting with the environment and external equipment such as walking aid. Other kinds of fall (slip, side fall and sit to fall) must also be tested to evaluate its robustness.

Chapter 4

Design and Characterisation of Base-suit

A base-suit is the underlying webbing system that creates anchor(attachment) points on the body to effectively transmit forces from the actuator to the body with minimal loss. The ideal base-suit should be thin and light, and be worn under regular clothing and while not being seen.

Stiffness or the body's elasticity under pressure is the most significant factor that affects the force transmission efficiency of the base-suit. The best solution is to direct all forces straight to the skeletal structure, bypassing all the soft tissues surrounding it. However, that is humanly impossible; hence, the alternative is to model and evaluate the human body stiffness, in order to optimise the base-suit and actuator design. However, the human body is anisotropic, and the muscle stiffness changes with every contraction and posture, making it impractical to measure stiffness in every direction, posture, muscle state and fatigue state. Therefore the best concession is to measure stiffness along the path and direction of the eventual force vector, along with the stiffness that exists within the actuator and base-suit itself [136]. Although this approach simplifies the measurement, any modification to the design of the base-suit will require a new measurement. Therefore, a method of estimating stiffness from readily available body parameters (body weight, BMI, etc.) is proposed. The outcome of this method will allow the required force input per unit of the desired deformation to be estimated and vice versa.

This chapter starts by describing the considerations and rationale of choosing commercial safety harnesses as the base-suit. Next, a method of controlling base-suit tightness is proposed, as the tightness significantly affects the measured stiffness. This is followed by a discussion and proposed solution of the problem on measuring the coupled body motion and force independently. Finally, different methods of

stiffness estimation using the measured strain and force are evaluated.

4.1 Base-suit Design

Elasticity can appear from the all components of the system:

- Actuator
- Force transmission cable
- Exosuit and its anchor points
- Subject's static body
- Subject's interaction with the device

The human body remains the component with the least stiffness, and the entire system's stiffness is as stiff as its least stiff material; hence, it is logical to focus on designing a base-suit that can increase the body's stiffness. The human body has areas of low stiffness around regions which are covered with soft tissues. When motion of the subjects are also considered, muscle and bone movements create more stiffness variation that is difficult to consider and tracked. Hence, a base-suit that is designed to increase stiffness along a few anchor points (points where actuators will be attached), is sufficient. It is not necessary to design a base-suit that can increase stiffness all around the body.

The first prototype of the base-suit is made by combining 2 commercially available chest and seat harnesses meant for rock climbing (specifications listed in Appendix G.2 and G.3). They were chosen for the following reasons:

- Manufactured to withstand substantial loading, and hence a high factor of safety
- Made from nylon webbing and metal buckles, and hence high stiffness
- Designed to leverage on the large load bearing skeletal segments of the human body, therefore protecting delicate organs
- Webbing has a high surface area. When routed through areas of the human body with relatively thin soft tissue layer, it provides better comfort while maintaining sufficiently high stiffness for the suit-body system
- Simple to wear and adjust

Figure 4.1: Front and rear view of the harness being worn. Additional webbings (orange) were added to improve on the apparent stiffness of the base-suit.

4.1.1 Force Vector Requirement

Due to the anisotropic properties of the body, stiffness measurement of the base-suit must be done accordingly for the intended application. Hence, actuators that create the proper force vectors on the subject's body must be worn to induce the related system deformation. The torso assistive forces have been identified as the most critical factor for the current application of fall recovery (Section 5.2). Consequently, this determines the moment arm of the actuator, the force vector, and therefore, the combined measured stiffness.

The actuator induces torso deformation by shortening a cable (wire rope) between 2 anchor points on the body. An actuator mount is used for mounting a previous prototype of the actuator (Figure 4.2), at a perpendicular distance of 106 mm away from the back of the pelvis.

4.1.2 Fitting Measurement

Apart from ensuring that proper force vectors are used to induce the system deformation for stiffness measurement, the fitting or tightness of the base-suit also affects the overall stiffness of the system. A loose base-suit allows for much higher deformation than a tight base-suit under the same applied force vector. A method

Figure 4.2: (a) actuator mount on the waist belt. (b) actuator attached on the mount over the waist belt. Additional webbings(orange) are added to improve stability of actuator.

for measuring the base-suit tightness must be proposed to ensure experimental repeatability and to proper quantitative analysis.

The proposed measurement method is to use an air-pack sensor to measure the tightness of the base-suit (Section 2.6.2). The air-pack can follow the contoured surface of the body while retaining its deformability to allow for force measurement. However, since the air-packs are not readily available on the market, a children's sphygmomanometer is used as an alternative (Figure 4.3, specifications are listed in Appendix G.4).

Figure 4.3: Sphygmomanometer used for fitting measurement

Fitting Procedure

The procedures for measuring the fitting of the base-suit starts with calibrating the air pack. A 500g weight is placed on the air pack to ensure that sufficient air volume is reached for deformation, but not too high until the air pack cannot be inserted

under the webbings. Next, subjects will wear the chest and seat harness loosely. The air pack will then be placed on the subject in the order of chest, shoulder, waist and thighs; tightening each strap to the desired pressure at each location before proceeding to the next location. Details are stated in Appendix H.

20 subjects were used in this experiment. They were all males with an average age of 27.4 ± 6.2 years, average height of 173.65 ± 5.97 cm, average weight of 68.24 ± 12.7 kg, and an average BMI of 22.53 ± 3.36 . The average tightness pressure reading of the base-suit from 20 subjects is listed in Table 4.1.

Table 4.1: Average pressure (mmHg) and its standard deviation between different body parts and the base-suit.

	R Shoulder	L Shoulder	Chest	Waist	R Thigh	L Thigh
Average Pressure	51.45	51.5	21.65	47.5	27.35	27.25
Standard Deviation	3.15	2.84	3.31	5.76	3.29	3.14

4.2 Force loading and Measurement

Stiffness is defined as:

$$Stiffness = Force \text{ applied} / Displacement \quad (4.1)$$

However, stiffness cannot be measured directly, as it is very challenging to measure the displacement accurately on the subject. Displacement on a human typically involved skin deformation and muscle displacement, complicating the process of measurement. Additionally, the displacement on the human is insufficient to model the system as it does not include the deformation that exists in the mechanical system.

Conventionally, stiffness is calculated by moving two rigid plates towards/apart from each other with the material of interest between them. The force is accurately controlled with relatively little deviations caused by material deformation. Young's modulus is calculated by dividing the stress (σ , force over material's cross-sectional area) by the strain (ϵ , deformation) Equation 4.2

$$\sigma_s = E\epsilon \quad (4.2)$$

where σ_s is stress (pressure); ϵ is strain (deformation), and E is Young's modulus.

Complications arise when stress and strain are both measured simultaneously on the body. This is because there are 2 dependent sources of force acting on the system (Equation 4.3). The first force (F_{act}) is created by the actuator, which can be accurately measured. The second force is the subject's muscular force (F_{torso}), which is affected by the actuator force to a varying degree.

$$F_{act} + F_{torso} = K \Delta L_{base-suit} \quad (4.3)$$

where F_{act} and F_{torso} are forces from the actuator and lumbar flexion; K is the stiffness ratio; and $\Delta L_{base-suit}$ is the combined deformation of the base-suit, actuator and subject's body.

An example of the actuator affecting the muscular contraction of the subject happens when subjects are asked to keep a static pose of 30 deg hip flexion, with an initial zero deformation between the two anchor points at the back, and zero contraction force between the two anchor points. When the actuator activates with 10N of force, it shortens the cable between the two anchor points to 2cm. However, that contraction force may also cause the body to extend, reducing the applied force and hence affecting the stiffness measurement process. As a result, there is no way to determine the stress and strain of the system simultaneously.

A new method is proposed to measure the stress and strain separately. This is done by using the hip flexion angle to decouple the effect of the actuator force (F_{act}), hip flexion force (F_{torso}) and the system's deformation. At any chosen hip flexion angle, a constant force and deformation can be reached. Therefore, by keeping the deformation constant, a varying force can be observed using varying flexion angle and vice versa.

4.2.1 Decoupled Force Measurement

This experiment keeps the amount of deformation constant while making use of the hip flexion to generate the force. The actuator is not used to generate the necessary force because it causes the distance between the anchor points to change.

The top anchor point is situated at the T5 spine position at the back, and the bottom anchor point is the output of the actuator which is mounted at the S1 spine position during initial setup conditions. A force sensor (Appendix G.5) is connected in series to measure the tension on the cable (Figure 4.4). Although the anchor point on the body will shift during compression, it is accounted for as part of the stress measurement in all the subjects by using a consistent base-suit tightness.

Figure 4.4: Mounting of a force sensor between the torso and seat harness to measure force while keeping constant strain.

The subject adopts a static vertical pose (90 deg) before the actual force measurement. The connecting cable between 2 anchor points is fixed. An IMU attached on the chest measures, which constantly informs the subject to keep a constant lumbar flexion. Experiment starts from the vertical position (90 deg) and subject will flex in decrements of 5 deg until 30 deg. The tension on the cable is recorded at every flexion interval (cable length does not change). The detailed process of the decoupled force measurement is stated in Appendix I.

This experiment gives the measurement of the entire system stiffness at a constant length. A subject with highly toned muscle will generate higher tension on the cable between the two anchor points than a lesser toned and overweight subject. This is due to the muscle having higher stiffness than fats. Therefore, it allows for the estimation of body stiffness if all other system factors are kept constant. However, the deformation at every flexion value is still unknown.

4.2.2 Decoupled Deformation Measurement

This experiment keeps the amount of cable tension to a constant minimum to prevent slack while using hip flexion to determine the initial cable length at different flexion angles. The setup of the experiment is similar to the decoupled force measurement (Section 4.2.1), with only the cable tension being kept at a constant minimum of 15N throughout the experiment. This 15N tension is chosen only to ensure that there is no slack in the cables while remaining relatively loose. Then, subjects were requested to flex at 90 deg and in decrements of 5 deg until 30 deg. At every flexion interval, the cable between the two anchor points is adjusted until the tension of the cable is at 15N. This allows the ideal length of the cable at every flexion angle to be measured.

Strain can be calculated by subtracting the length of the cable during deformation measurement from the fixed cable length in force measurement. A detailed description of the decoupled deformation measurement is stated in Appendix I

4.3 Linear Stiffness Estimation

The measurement results from one of the subjects obtained from the decoupled force and deformation measurement are shown in Table 4.2. Notice that the last row is calculated by subtracting the original length of the cable in decoupled force measurement (7.75 cm) from the decoupled deformation measurement.

Table 4.2: Sample of decoupled force and deformation measurement.

Flex angle (deg)	90	85	80	...	40	35	30
Decoupled Force @ 7.75cm (N)	15	21	30	...	133	157	182
Decoupled Extension @ 15N (cm)	7.75	8.5	10	...	17.75	19	20.5
Change in Extension (cm)	0.0	0.75	2.25	...	10.0	11.25	12.75

Linear stiffness is estimated as:

$$K = F / \Delta L_{base-suit} \quad (4.4)$$

where in this case, F is the decoupled force (F_{act} and F_{torso}) and $\Delta L_{base-suit}$ is the change in extension (deformation). Using linear regression, the best fit linear line is plotted for first 10 of the 20 subjects as shown in Figure 4.5 (only 10 subjects are presented for clarity). The goodness of fit is evaluated via Coefficient of Determination

(CoD) or R^2 (Equation 4.5).

$$R^2 = 1 - \frac{\sum_{i=1}^n (F_i - \hat{F}_i)^2}{\sum_{i=1}^n (F_i - \bar{F})^2} \quad (4.5)$$

where F_i is the collected force data, $\hat{F}_i$ is the force data from the fitted curve and $\bar{F}$ is the mean of the force data.

Figure 4.5: Force versus deformation for the first 10 subjects. Each subject is labelled as S^* , where $*$ is the subject's number. Linear regression was performed on each subject.

The CoD (R^2) of the linear fitted curve is shown in Table 4.3.

Table 4.3: Linear regression of decoupled force and deformation measurement.

Subject	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
R^2	0.921	0.919	0.915	0.949	0.826	0.928	0.970	0.959	0.954	0.935

4.3.1 Inter-Subject Stiffness Estimation

At first glance, the CoD (R^2) for each of the subjects is very high (average of 0.9276), indicating a good fit with the linear fitting. However, when performing a linear regression on the combined data points of all 20 subjects, a less satisfactory R^2 value of 0.8241 was obtained (Figure 4.6a).

With the combined linear stiffness relationships, forces can be estimated based on the deformation values, even on new subjects who have not undergone the de-

Figure 4.6: (a) Force versus deformation for the combined dataset of 20 subjects. A linear regression is performed on the dataset; (b) Residuals of linear stiffness model versus empirical force at different deformation value

coupled force and deformation measurement. The resultant residuals (the difference between the collected samples and the fitted model) for all 20 subjects are shown in Figure 4.6b. An average residual of $13.28N$, a maximum residual of $72.83N$, with a standard deviation of $18.07N$.

4.4 Polynomial Stiffness Estimation

Closer inspection of the data points reveals a polynomial trend in the force versus deformation chart. This is logical as the body is made up of fats, muscles and bones. At low tension, the muscles are not activated, so only the fats get deformed. At higher tension, muscles activate to resist the force leading to a higher deformation with the same force increment. As such, a quadratic polynomial regression might provide a better fit with the data. The fitting results of 10 subjects are shown in Figure 4.7. The average CoD (R^2) is shown in Table 4.4, with an increase from the linearly regressed 0.9276 to the polynomial regressed 0.992.

Figure 4.7: Force versus deformation for the first 10 subjects. Each subject is labelled as S^* , where $*$ is the subject's number. A polynomial regression is performed on each subject.

Table 4.4: Quadratic regression of decoupled force and deformation measurement.

Subject	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
R^2	0.992	0.991	0.995	0.998	0.997	0.997	0.996	0.970	0.990	0.994

4.4.1 Inter-Subject Stiffness Estimation

The improvement of all subject's R^2 value indicates that the human body has non-linear stiffness. However, a general model with 20 subjects produces a resultant

CoD of 0.8469, which is only a slight increase over the CoD of 0.8241 from linear stiffness fitting (Figure 4.8a).

Figure 4.8: (a) Force versus deformation for the combined dataset of 20 subjects. A quadratic polynomial regression is performed on the dataset; (b) Residuals of linear stiffness model versus empirical force at different deformation value.

The resultant residuals for 20 subjects are shown in Figure 4.8b. An average residual of $11.27N$, a maximum residual of 71.50 , with a standard deviation of 17.05 ; a slight decrease over the linear stiffness model.

4.5 Neural Network Model with body parameters

Looking at the results from the linear and polynomial regression, one can easily observe that stiffness estimates are accurate for individuals. However, significant residuals emerge when creating a generalised stiffness model, indicating that variables that describe inter-subject variability have not been taken into account.

An important factor that was not included in both linear and polynomial fitted model is the body parameter. Logically, body parameters such as weight, height, body fat and muscle percentage will affect the stiffness of the body. Given that all other perceivable mechanical variable has been controlled, a better model can be obtained by accounting for the body parameters.

Conventionally, the proper method of determining relationships between different parameters is to vary one parameter while keeping the others constant. However, it is quite impossible to find subjects that differ in only one body parameter from each other. Hence, neural network is employed to evaluate multiple factors simultaneously. The disadvantage associated with NN is often cited as the trained network is a black-box that cannot be understood. Therefore, an attempt to estimate the variable importance is explained in Section 4.5.2. Another drawback of the neural network is the requirement of a large dataset for accurate prediction. With the data from the 20 subjects mentioned above, a total of 780 data points were obtained.

The neural network architecture used in this study consists of 1 input layer, 2 hidden layers and 1 output layer. The number of nodes from input to hidden to output layers were 21, 15, 5 and 1 respectively (see Figure 4.9). The activation function of each neuron was a sigmoid function, and the loss or objective function was the Euclidean loss function (Equation 4.6). Only 2 hidden layers were used, as 3 compounded layers of linear weights and bias were sufficient to model the non-linear stiffness of the body. This assumption stemmed from the observation that a quadratic polynomial was sufficiently accurate to model an individual's deformation to force relationship (see Section 4.4).

$$loss = \frac{1}{2N} \sum_{i=1}^N ||y_i - \bar{y}_i||^2 \quad (4.6)$$

where N is the number of outputs in a batch size, y_i is the network output and $\bar{y}_i$ is the training data output.

Adam solver [187] was chosen as the solver of choice for the current dataset with stochastic gradients. Moreover, *Adam* can keep the update weights stable, while

Figure 4.9: The neural network used in the study of force versus extension relationship

making the learning faster with greater accuracy. *Adam* solver can be described as follows:

$$\begin{aligned}
 m_{ti} &= \xi_1(m_{t-1})_i + (1 - \xi_1)(\nabla L(W_t))_i \\
 m_{t2i} &= \xi_2(v_{t-1})_i + (1 - \xi_2)(\nabla L(W_t))_i^2 \\
 (W_{t+1})_i &= (W_t)_i - \alpha \frac{\sqrt{1 - (\xi_2)_i^t}}{1 - (\xi_1)_i^t} \frac{m_{ti}}{\sqrt{m_{t2i}} + \epsilon}
 \end{aligned} \tag{4.7}$$

where W are the weights, $(\nabla L(W_t))_i$ and $(\nabla L(W_t))_i^2$ are the first and second gradient of the weights, ξ_1 and ξ_2 are the exponential decay rates for the moment estimates, m_t and m_{t2} are the first and second moment vectors. The values used for this study are as follows:

$$\begin{aligned}
 &\text{Learning rate, } \alpha = 0.02 \\
 &1^{st} \text{ moment decay rate, } \xi_1 = 0.9 \\
 &2^{nd} \text{ moment decay rate, } \xi_2 = 0.999 \\
 &\text{base } 2^{nd} \text{ moment, } \epsilon = 10^{-8}
 \end{aligned}$$

Caffe [188] was chosen as the library of choice to implement the neural network.

Neural Network Inputs

The body parameters inputs were measured using a body composition monitor (Omron HBF-375, Appendix G.6). Table 4.5 shows the list of 20 parameters used.

Table 4.5: 20 body parameters used in stiffness estimation.

Body Parameters		
Age	Height (cm)	Weight (Kg)
Total fat (%)	Visceral fat (%)	BMI
SF Body (%)	SF Trunk (%)	SF Arms (%)
SF Legs (%)	SM Body (%)	SM Trunk (%)
SM Arms (%)	SM Legs (%)	R Shoulder pressure
L Shoulder pressure	Chest pressure	Waist pressure
R Thigh pressure	L Thigh pressure	

SF represents Subcutaneous Fat, and SM represents Skeletal Muscle. Body parts pressure indicate the fitting of the base-suit and are measured in mmHg.

The inputs to the network are then the 20 body parameters and the deformation value (21 total input nodes). The output will be the force value. However, they must be scaled between 0 to 1 to prevent saturation at the limits of the network. Table 4.6 shows the scaling used for each of the parameters.

Table 4.6: Scaling values used for 20 body parameters, deformation and force values.

Parameters	Scaling
Age	1/100
Height	1/200
Weight	1/100
All Percentages	1/100
Shoulder, waist pressure	1/100
Chest, thigh pressure	1/50
Deformation	1/20
Force	1/200

4.5.1 Neural Network Results

Similar to the linear and polynomial stiffness models, data from all 20 subjects were used training and validation of the neural network model. Each subject performed one decoupled deformation measurement (13 intervals) with three corresponding

decoupled force measurements. This produced 39 data points for each subject. A total of 780 data points are obtained with 20 subjects for the network input.

Training of the network is performed on the first 18 subjects, and the remaining 2 subjects are used to test the accuracy of the network. The trained network produced an average trained Euclidean loss of 65.78N, with the individual residuals shown in Figure 4.10. The standard deviation of the force residuals is at 11.470N, and the maximum force residual is at 78N.

Figure 4.10: Residual of neural network versus empirical force at different deformation value.

Results performed using the remaining 2 test subjects are shown in Figure 4.11a (force versus deformation) and 4.11b (residual plot). The maximum force residual is at 76.34N, with standard deviation of 28.953N.

From the residual plot (Figure 4.11b), it can be observed that the neural network can accurately predict forces at the middle deformation range, but it fails to perform as accurately at the lower and higher limits of deformation values.

4.5.2 Variables Contribution

A disadvantage of using Neural Network is the importance of each input variables are often unknown, limiting its usefulness for understanding the contributing factors to a certain phenomenon [189, 190]. Contributing factors remain unknown because it is hard to disentangle the importance of each factor from the highly intertwined network. Several methods have been proposed to tease out the factor's importance [189, 190], but a simple and yet efficient method for small networks has been to drop a single input and retrain the network. By observing how the network

Figure 4.11: (a) Neural Network output versus empirical force; (b) Residual of neural network output and empirical forces at different deformation value.

loss/accuracy changes for each dropped input, it can determine a factor's importance. Important factors will have a higher loss or lower accuracy.

For this network, each factor is zeroed and retrain for 10 times before averaging the Euclidean loss. This is necessary as the weights and biases of each input are randomly chosen based on a unit Gaussian distribution. The randomness of initial weights and biases prevents the network from converging at a local optimum. The results of this test are shown in Table 4.7.

As expected, deformation is the most critical factor that determines the force. Next is the skeletal muscle percentage of the trunk, which is associated with the

Table 4.7: Euclidean loss of each factor

	Test number							
Factor	1	2	3	...	8	9	10	avg loss
Deformation	19.73	22.02	20.09	...	20.27	22.06	21.95	21.20
SM Trunk	3.53	1.86	11.90	...	5.67	6.84	5.23	5.47
Shoulder R	4.63	5.87	3.48	...	1.99	3.47	8.65	5.18
Visceral fat	2.80	5.08	3.09	...	4.08	2.81	6.59	4.91
SM Arms	2.96	3.74	3.13	...	7.04	5.58	1.72	4.72
SM Body	5.01	5.12	11.09	...	3.32	2.61	5.38	4.38
SF Arms	1.75	4.24	4.16	...	4.65	5.47	5.88	4.36
Total fat	4.64	4.95	1.62	...	3.41	5.24	3.58	4.29
Weight	4.58	2.39	2.69	...	7.19	1.52	7.75	4.15
Height	3.00	2.92	2.64	...	3.55	3.11	3.33	4.12
Thigh L	2.32	7.91	4.22	...	3.76	2.15	8.32	4.03
SF Legs	3.24	2.95	5.34	...	1.63	6.35	3.23	3.94
Thigh R	2.28	5.34	1.45	...	8.43	11.47	2.50	3.88
Waist	3.76	4.05	3.22	...	1.65	3.17	6.29	3.85
SF Trunk	3.60	5.54	2.66	...	2.73	2.97	2.75	3.73
BMI	3.09	2.00	4.24	...	2.61	6.83	4.46	3.67
Age	3.51	2.97	5.44	...	2.68	5.64	4.73	3.65
SM Legs	3.30	2.71	2.49	...	2.03	3.05	2.85	3.58
SF Body	3.79	2.07	2.73	...	5.51	2.71	2.28	3.45
Shoulder L	6.97	2.23	4.21	...	1.85	2.33	3.19	3.13
Chest	2.14	2.30	1.59	...	2.56	2.76	2.88	2.70

Losses indicated refers to the losses of the NN output force versus the empirical forces. The losses are listed with the magnitude multiplication of 0.001. Factors are listed from most important to least important. SF = Subcutaneous Fat, SM = Skeletal Muscle.

most observable deformation during lumbar flexion. A higher skeletal muscle percentage provides higher body stiffness, which reduces deformation. The next factor of importance is the right shoulder pressure, which supports the majority of the pulling force on the cable. Interestingly, the left shoulder is ranked 20th out of 21 factors, even though one might expect it to be the same importance as the right shoulder. This could likely be due to changes in pressure when tightening the chest harness. Routinely, the left shoulder harness is always tightened and measured before the right harness. The act of tightening the right shoulder most likely has reduced the tightness of the left shoulder. Hence during compression, the majority of the tension of the cable is supported by the right shoulder. Future studies must take into account this discrepancy, and measure both shoulder pressures again after

any adjustments to either shoulder.

The rest of the factors indicate that both muscles and fat are equally important in regulating the stiffness of the human body because the factors are intertwined among the rankings. Usual body characterisation indicators like height, weight and BMI do not affect body stiffness significantly.

4.6 Results Comparison

After performing linear, quadratic and neural network fitting, the resultant residuals and CoD (R^2) are summarised in Table 4.8.

Table 4.8: Comparison of different stiffness model using absolute residuals.

Model	Avg Force Residual	Max Force residual	Std Dev	R^2
Linear Stiffness Model	13.279	72.83	18.07	0.8241
Polynomial Stiffness Model	11.271	71.50	17.05	0.8469
Neural Network Model	7.556	77.952	8.630	0.9345

A conclusion can be made by looking at the CoD (R^2) between all the different models. Neural Network model is the most accurate in predicting force versus deformation values. This could be attributed to the inclusion of body parameters that allow the model to be individualised.

Since the proper usage of the model is to allow bi-directional conversion between force and deformation, a reciprocating neural network has also been trained. Deformation is obtained as output using the 20 body parameters and force as input. The trained network produced an average trained Euclidean loss of 0.394cm, with the individual residuals shown in Figure 4.12. The standard deviation of the deformation residual is at 0.586cm, maximum deformation residual at 4.62cm, average residual at 0.667cm and R^2 at 0.956.

The residual plot of the test trial using the remaining two subject is shown in Figure 4.13b and the deformation versus force output is shown in Figure 4.13a. The maximum deformation residual is at 5.819N, and its standard deviation of 28.953N.

Figure 4.12: Residual of neural network versus empirical force at different deformation value.

Figure 4.13: (a) Neural Network output versus empirical force; (b) Residual of neural network versus empirical force at different deformation value.

4.7 Chapter Conclusion

The results showed that a proper base-suit can be created out of 2 commercially available safety harness. Their force/deformation relationship can be modelled accurately on an individual level by both the linear and quadratic regression. However, a generalised equation cannot be determined as different characteristics of every individual has not been accounted. Hence, a neural network model was proposed to account for the individuals' body parameters.

At low deformation and force values, all 3 models (linear, quadratic and NN) can accurately predict the corresponding force and deformation value. Although the neural network model estimation is not as accurate at higher deformation/force, it still outperforms the other models in estimating the force and deformation values, with a lowest average residual of $7.556N$. This is 33% lower than the next better performing model. This is attributed to the network capability in being able to consider body parameters when estimating the force output.

The outcome of this study allows the investigator to estimate the force/deformation outcome by simply measuring the body parameters of the subject and inputting it into the neural network.

4.8 Future Work

The accuracy of the force-deformation relationship can be further improved by using more body parameters, body dynamics and subjects to train the network. Subsequently, a general equation that estimates the body stiffness without the NN can be developed to simplify force/deformation calculation.

Chapter 5

Design of a High Stroke, High Bandwidth, High Force and High Transparency Actuator

Chapter 4 describes and characterises the base-suit, which is the force transmission component of the exosuit. Here, the actuator, or the force generating component of the exosuit, is developed and discussed. This actuator is designed to only assist when necessary to preserve the natural walking pattern of the user. It must also have high force and bandwidth to provide sufficient forces during the short period before impact.

Although there are different kinds of commercially available actuator, none of them meets the stringent requirement for fall intervention. The ideal actuator for fall intervention solution should be fast, powerful, energy efficient and lightweight. Hence, a new type of actuator that is built upon constant force spring is developed.

In this chapter, the design considerations and rationale for developing a new kind of actuator are discussed. This is followed by evaluating the best force vector for fall intervention. Finally, the mechanical prototype and its effect on the subject is presented.

5.1 Design Considerations

Designing of the prototype starts with calculating how much stopping torque is required during a fall event. Balance can be recovered if the prototype is capable of arresting all unwanted forces and torque. If the prototype cannot fully arrest all unwanted forces, properly synchronised assistance will still reduce impact magnitude and increase the duration from fall initiation to impact. Nonetheless, improper

synchronisation of assistive force will superimpose with the unwanted forces and create a more severe fall.

The magnitude of forces required to arrest falls is usually unrecorded due to the random nature of fall occurrence. Hence, the forces required are inferred from joint moments calculated from a jump landing [191]. It is assumed that the forces required to land from a fall would be similar to those of landing from a jump. Only the joint moments in the sagittal plane are considered as this study focuses on balance recovery of frontal and backwards fall. The lumbosacral joint uses theoretical maximum isometric strength [192] as jump landing data were not found.

Table 5.1: Assistive forces and torque necessary to provide assistance during a near-fall scenario.

Joint	Stopping Torque (Nm)	Muscle Moment Arm (m)	Actuator Moment Arm (m)	Pulling Force (N)	20% Pulling Force (N)	Δ angle (deg)
Ankle	100 [191]	0.047 [193]	0.1	680	136	30 [194]
Knee	142 [191]	0.056 [193]	0.1	910	182	18
Pelvis	111 [191]	0.094 [193]	0.1	572	114	7
Lumbosacral	213 [192]	0.04 [195]	0.1	1521	304	30 [20]

Stopping torque is estimated from jump landing force; Muscle moment arms are obtained from various literature; Actuator moment arm is estimated based on the moment arm of a preliminary prototype; Pulling force is calculated by dividing stopping torque with the moment arm; Angle change (Δ angle) is estimated from maximum deviations between normal and perturbed walking for ankle, knee and pelvis angle; the angle change (Δ angle) for lumbosacral joint uses the maximum trunk fall recoverable angle [20]. The exosuit plans to assist around 20% of the pulling force.

Apart from the force requirement, weight is a big concern for the prototype as users need to carry it on their body all the time. Metabolic cost of the user increases by 7.5 – 8.5% per kilogram of weight added to the legs and 1 – 2% when added to the waist [129, 130]. However, the weight of this prototype is not constrained as multiple customizable features are built into the prototype for ease of individualisation and force adjustment. The weight will be significantly reduced after the effect of the actuator has been validated.

Other vital requirements include:

- Fast trigger response, given that trips initiate and end in about than 500ms while slips end in 1second

- User must be freely-movable when the prototype is not triggered
- Small in size and lightweight to increase the system's transparency
- Low power consumption to maintain prototype functionality as falls do not occur commonly. It is impractical to recharge actuator every day for a system used once per year.

Due to the low rate of falls at 0.65 times per year (see Section 2.1.1), the actuator can be designed to store sufficient energy for single use only. A recharge is required after every actuator activation. This feature is beneficial in reducing the weight of the exosuit.

5.2 Balance Recovery Strategies

As mentioned, synchronised actuator forces will assist in balance recovery, but unsynchronised assistance will be detrimental to the stability of the user. Therefore, force vectors and activation timing must be properly studied before actual implementation. The purpose of balance recovery strategy is to bring the CoM back into the BoS [51], and to decrease undesirable kinematics [20] generated during periods of instability.

Trips account for the majority of falls caused by external disturbances and incorrect weight transfer (see Section 2.2); hence, they are the focus of this study. Falls due to other internal factors such as sudden loss of muscle strength or consciousness will not be discussed, as they require full body weight support which is not achievable with the current state of soft robotics technology.

Falls are normally categorised based on their fall direction: forward, backwards and lateral [16]. Although no falls in real life will ever be purely single directional, it is useful to study their recovery strategies separately and combine them based on the fall direction vector decomposition. A trip is mostly a forward fall [16], and it has 2 recovery strategies: (1) Elevating strategy and (2) Lowering strategy (Figure 2.1). The activated strategy of choice depends on the gait phase at the instance of fall onset.

Repeated Figure 2.1: Recovery Strategies for forward fall. Image from Shiratori *et al.* [50]

5.2.1 Elevating Strategy

Elevating strategy happens in the early to mid swing phase, when the velocity of the lower limb is still accelerating in the swing phase. During this early swing phase, the rectus femoris of the swing leg is activated, pulling the leg forward. When perturbation occurs, the body's initial response is to stiffen the entire body [145]. This stiffening is caused by activation of both agonist and antagonist muscles, such as activating both rectus femoris and biceps femoris muscle of the swing leg to keep the leg in place. It is observed that rectus femoris only retains its initial state of activation (during the instance of fall) during the first 80ms of the trip [49, 196]. Hip flexion occurs to widen BoS and raise the swing leg only after the central nervous system has processed the stimulus. During which, the antagonist biceps femoris gets inhibited, causing hip flexion to occur (Figure 5.1). In addition, the support limb (contralateral stance limb) will perform hip extension after the nervous system has processed the stimulus. This increases floor clearance height, while also increasing the air-time of the body to provide longer duration for the recovery limb (ipsilateral swing leg) to widen the BoS [51]. The overall observable outcome of this activation sequence is that the whole body stiffens at the beginning, while the legs widen and raise higher after a short duration to avoid the obstacle causing the trip (Figure 2.1).

Figure 5.1: Muscle responses of major hip flexion (rectus femoris, RF) and extensor (biceps femoris, BF) muscles during a trip Blue muscles represent low activation muscles, and red muscles are highly activated muscles. (a) During swing phase initiation, the RF muscle is activated to accelerate the leg forward. (b) During early to mid swing, the BF muscle is still inhibited to allow hip flexion. (c) When a trip occurs, both the RF and BF muscles get activated to the same level to increase body stiffness, preventing further unwanted limb movements. (d) Only after the nervous system has processed the stimulus, that the BF muscle gets inhibited to allow more hip flexion to occur. At this instance, the RF muscles have increased activation to widen the base of support further. (e) This increased activation extends until the late swing phase, where the swing leg touchdown and the rest of the undesirable fall dynamics is handled by the torso.

After the touchdown of the swing leg, the remaining undesirable kinematics induced by the trip is handled by the lumbosacral joint [20]. However, the base of support has already been widened, reducing the burden imposed on the paraspinal muscles.

5.2.2 Lowering Strategy

Lowering strategy occurs at the mid to end swing phase when the swing leg is depending on the momentum gained during the early swing phase to widen the stride. Similar to the elevating strategy, the first response upon perturbation is to stiffen the body, preventing the legs from deviating away from its intended position [196]. After the nervous system has processed the stimulus, the ipsilateral swing leg is lowered before the obstacle. Next, the contralateral stance leg transition into the swing leg by pushing off, widening the BoS (Figure 2.1). The perturbed leg now becomes the support leg and provides plantar flexion and knee extension to lift the body upwards for elevated toe clearance and increase air-time for the new swing leg (see Figure 5.2). The rectus femoris of the new swing leg is activated to generate hip flexion. Although a small number of subjects did perform elevating recovery motion at late swing phase [49, 196], the chances of successful toe clearance is small as the body is already undergoing a downwards and forward motion due to gravity

and its GRF point being far behind the centre of mass.

Figure 5.2: Muscle responses of major hip flexion (rectus femoris, RF), hip extensor (biceps femoris, BF) and knee extensor (soleus, SO). Blue muscles represent low activation muscles, and red muscles are highly activated muscles. (a) During the late swing, the RF and BF are already non-activated. Upon contact with an obstacle, all the muscles stiffen up while waiting for responses from the nervous system. (b) Signals from the nervous system will then activate the BF and SO to quickly lower the swing leg. (c) This is to allow for a quick transition to stance leg, allowing the contralateral leg to start swinging as soon as possible.

After the contralateral swing leg has performed the swing phase and touchdown, the torso will take over to reduce the remaining undesirable kinematics of the trip [20].

5.2.3 Torso Extension

The paraspinal muscles of the torso play a vital part in reducing and eliminating unwanted AngMom during the pre-touchdown and post-touchdown trip phase respectively. During the pre-touchdown phase, the paraspinal muscles contract to prevent the induced forward AngMom from generating excessive lumbar flexion. After the touchdown, before the body has come to a stable position, the larger than normal impact of the touchdown leg gets transferred to the upper body and induces another round of lumbar flexion. The paraspinal muscles are now required to eliminate the unwanted AngMom fully, or the body has to take another step to shift the CoM behind of the GRF.

This strategy of torso extension is valid for both early-mid (elevating strategy) and mid-late trips (lowering strategy). This is because both trips generate unwanted forward AngMom that can be reduced and eliminated via torso extension.

5.3 Actuator Placement

From the recovery strategies described for trips, it is recognised that the actions undertaken were all manipulation of the CoM to GRF vector. The subject will feel a

forward or backwards rotation depending on whether the projected GRF is in front of or behind the CoM (Figure 5.3)

Figure 5.3: Generated body movements due to the effect of GRF (without friction) on different CoM positions. In (a), GRF is anterior of the CoM, leading to a backwards moment, reducing angular momentum in a trip. In (b), GRF is posterior to CoM, creating a forward moment, which increases the risk of falling during a trip.

A method of assisting the control of the CoM to GRF vector is to add actuators to ankles, knees and hip joints, which results in at least 6 multi-axis actuators on the user (Figure 5.4). This solution is not ideal as the high number of actuators increases the weight of the system. The metabolic cost of adding an extra kg of mass to the foot is a 7.5% to 8.5% increase over the initial metabolic cost, compared to 1% to 2% increase when an extra kg is added to the waist [129, 130]. Instead, a single actuator mounted on the torso is proposed to reduce the number of necessary actuators and allow for nearer waist placement (Figure 5.5). A single torso actuator is capable of providing position control of the CoM during a fall because the torso constitutes about 50% of body weight, and thus will have more influence than the combined 20% of the thigh, shank and feet.

In addition to the weight advantage of using a single torso actuator for balance recovery, the effectiveness of a torso actuator is the largest for CoM manipulation. This is because 68% of the human body weight is above the hips [170], making the dynamic effects of the torso movement much more pronounced than the other limbs.

Moreover, there is a longer operation window for the torso actuator to perform,

Lower Limbs Widening

Figure 5.4: Lower Limbs Widening Fall Intervention solution. The assistive forces mounted on the lower limbs widens the BoS during the swing phase. This widened BoS will capture the CoM in a successful fall intervention scenario.

Torso Extension

Figure 5.5: Torso Extension Fall Intervention solution. The assistive forces that induces torso extension leads to a backwards shift of the CoM towards the centre of the BoS.

relative to the other lower limbs actuators, because the torso extension is required during both the pre-impact and post-impact phases. In all elevating and lowering strategies, the function of the lower limbs is to widen the base of support from trip initiation until the swing leg touches down. After touchdown, the lower limb will remain static while supporting the force of the torso. On the other hand, the torso

has the entire period from trip initiation to post-touchdown to eliminate the fall-induced dynamics.

Torso actuator also allows the same assistive force profile to be used for both early-mid and mid-late swing phase trip. This reduces the complications required from the fall detection algorithm to differentiate the gait phase at fall onset. Subjects may also choose to adopt the multi-step strategy to perform recovery motion [91]. However, the preference for using a multi-step strategy varies significantly across multiple subjects and different scenarios. If a lower limb actuator decides to assist on a multi-step strategy while the user is only adopting a single step strategy, the base of support will be broken, leading to an even higher risk of fall. On the contrary, the torso can assist the user in reducing unwanted angular momentum and generating opposing torque in both single and multi-step recovery strategies. Hence, creating a balance recovery system with a torso actuator is much more logical than other limbs. A summary of reasons to use torso actuator over lower limbs actuators is shown in Table 5.2.

Table 5.2: Torso vs Lower Limbs actuators for balance recovery assistance

Torso Actuation	Lower Limbs Actuation
Lighter weight as only one actuator is needed	Heavier as multiple actuators required
Longer operating window	Shorter operating window
Manipulate CoM	Manipulate BoS
Same assistive force profile for both elevating and lowering strategies	Different force profiles for elevating and lowering strategies
Same assistive force profile for multi-step strategy	Different assistive force profiles for multi-step strategy

Although torso actuator is the chosen actuator, actuators for other joints will be considered in the future. A rendition of the full exosuit is shown in Figure 5.6. Figure 5.7 shows the sequence of coordinated movements for trip recovery using torso and thigh actuators. The aim is to reproduce the effect of the support limb and torso CoM control by reducing fall initiated angular momentum and increasing stride length.

Figure 5.6: Design of Exosuit for balance recovery. Bowden cables are used to transmit actuator force output to joints; webbings are used to anchor the Bowden cables on the body; pre-loaded spring mechanisms are used to drive the Bowden cables. IMUs are attached on to the trunk and thigh of the subject for fall detection. More IMUs may be added to the ankle to improve accuracy.

Figure 5.7: Sequence of movement for a forward trip. (a) An obstacle in early swing phase trips the user; (b) the user raises swing leg to clear obstacle, and his CoM is leaving the BoS; (c) the user swings the swing leg forward to widen BoS with assistance from the Exosuit (transmitted forces shown with blue arrows); (d) after the front foot touches down, the Exosuit enhances the stability via torso extension to shift the CoM towards the centre of BoS.

5.4 Mechanical Prototype

Based on the requirements listed in Sections 5.1 to 5.3, an actuator has been developed. The main characteristics of the actuator are as follows:

High Bandwidth: The actuator is capable of providing large force in an instant

due to the use of CFS

High Constant Force: The actuator can output a constant, high magnitude force immediately from the use of multiple CFSs

2-Stage Stroke: The actuator is capable of providing 2 stages of stroke using the sequential release of different CFSs. This largely increases total stroke in a compact design

Low Power Consumption: Power is only required instantaneously for the release of energy stored in the actuator

High transparency: Excluding the weight of the actuator, the system has very high transparency as the subject can move freely while the cable attached to the user is only kept slightly taut

Customizable: The actuator is built with customizability in mind, having multiple threaded holes to allow for easy adjustments of the CFS stroke and force

Single use: The stored spring energy needs to be recharge manually by the user after each release

The actuator is made up of 5 CFS (Figure 5.8). The size and number of CFSs can be changed and according to the current force requirement of the experiment. The CFSs are obtained from Misumi (CFS2.4) and Lee Spring (LCF 040 20 125S). A single linear guide (Misumi, SSE2BSZ16G-190) with 2 rolling stages sit between all of the CFSs. One CFS is mounted onto the first stage of the linear guide, while 4 CFSs are mounted on the second stage. The spools of CFS are fixed in position by a rod at the end of the enclosure, and it will be unwound when the 2 stages are pulled away from the CFS spools. The pulled CFS stages are then held in place at the opposite end of the enclosure by 2 electromagnets (Aliexpress, P40/29K). The electromagnets require power (energise) to demagnetise but no power when holding the extended CFS spools; hence, power is only required momentarily to release the springs. Additionally, there are 2 rope cam cleats (Aliexpress, Ball bearing Cam Cleat, with a max working load of 135kg) attached to the top of the linear guide stages. A climbing rope (6mm, 900kg max load) runs through both of the cam cleats. One end of the rope is attached to a smaller CFS (Misumi, CFS0.6) and the other end is attached to a Bowden cable before attaching it onto the subject. The purpose of

Figure 5.8: The newly designed actuator that has a dual stroke system. Electromagnets hold the CFS in tension while it pulls on the rope cleats. Upon releasing the magnets, the cleats are pulled back by the CFS, pulling with it the rope.

Figure 5.9: The actual prototype of the actuator.

the smaller CFS is to keep the rope slightly taut even when the subject is moving. A picture of the actual prototype is shown in Figure 5.9.

The overall operating sequence of the actuator is separated into the charging sequence and releasing sequence. The charging sequence is responsible for extending the 2 stages of CFS and attaching them to the electromagnet. During the releasing sequence, the electromagnet of each stage is released sequentially, allowing the CFS to contract, thereby applying force onto the subject via the output rope.

5.4.1 Charging sequence

The actuator is made up of 2 stages of actuation. The first stage has one CFS for applying compression on low stiffness exosuit components and the subject. The second stage has four CFSs to apply the bulk of the force on the compressed body, improving force transmission efficiency. Charging of actuator is conducted in the sequence of 2nd stage to 1st stage.

When the CFS is not extended, the linear guide stages which are attached to the CFS endings, are sitting on the left side of the enclosure (Figure 5.10a). At this fully discharge configuration, both cam cleats are grabbing onto the rope, with excess rope between them. By pulling on the rope, the 2nd stage cam cleat can be pulled away from the CFS spool, and extends (charging) the 4 CFS (Figure 5.10b).

Opposite the 2nd stage CFS spools are 2 magnets that is waiting to hold onto the 2nd guide stage. As the 2nd guide stage gets attached to the magnet, the cam cleat is opened up by a ledge above and next to the magnet. This allows the rope between the 2nd stage's cleat to flow freely. However, the other end of the rope is still attached to the 1st stage's cam cleat. The CFS on the first stage can be extended by continuing to pull on the same rope (Figure 5.10c). Similarly, the 1st guide stage will be pulled until it is attracted to its corresponding magnet, and the 1st stage's cam cleat will be opened simultaneously. The rope is now only attached to a small CFS that is responsible for keeping the rope minimally taut. The actuator is now fully charged and ready to be released. The whole charging sequence for both stages can be performed in one smooth rope pulling motion.

5.4.2 Releasing sequence

Energy from the actuator is released in 2 stages. Releasing happens in the exact reverse chronological sequence as the charging sequence (1st stage then 2nd stage). However, the timing and sequence of demagnetising the electromagnet are crucial. To release the 1st stage, its corresponding electromagnet is energised (demagnetised) first (Figure 5.10c). This allows the 1st stage to be pulled away from the ledge, allowing its cam cleat to grab onto the rope and pull the rope inwards. This stage is only made up of 1 CFS. When the rope is attached to the subject via a Bowden cable, the 1st stage is responsible for reducing the compliance of the system, thereby allowing the 2nd stage to perform actual work.

After the 1st stage has reached the end of its stroke, the 2nd stage's holding magnet will now be energised (demagnetised), releasing its cam cleat from its ledge

Figure 5.10: The operating sequence of the actuator. For charging, the operation goes from (a) to (c). For releasing, the operation goes from (c) to (a).

(Figure 5.10b). This allows the 2nd stage's cam cleat to grab hold onto the rope and pull on the subject until its stroke has ended (Figure 5.10a). The stroke of the 1st and 2nd stages are adjusted by changing the electromagnet position closer or further away from the CFS.

The purpose of using a Bowden cable is to link the subject with the actuator while preventing the subject from being pulled towards the actuator when the actuator is released. The Bowden cable has an inextensible sheath that prevents the subject from being pulled back, thereby allowing the force output from the subject to be directed at performing torso extension only.

5.4.3 Characterization

The characteristics of the actuator are performed using a force sensor (Appendix G.5) on the output end of the rope. The force sensor is fixed relative to the actu-

ator enclosure, and the CFS stages were released sequentially. The rope output is attached to the sensing end effector of the force sensor. The maximum force output for 2 different actuator configurations were tested (Table 5.3).

Table 5.3: Force output of stages 1 and 2 with 2 different configuration.

	Stage 1: 2.4kg	Stage 2: 2 x 2.4kg
Average Max Force (N)	42.50	92.36
Standard Deviation	1.53	4.33
	Stage 1: 2.4kg	Stage 2: 4 x 2.4kg
Average Max Force (N)	47.12	183.90
Standard Deviation	3.80	7.09

For a single CFS, the theoretical force output is $23.5N$. However, the force output in Table 5.3 does not match this value. This is attributed to the impact force of the CFS as the force sensor is measuring the peak force output and not the steady state force. Additionally, the force experienced by the sensor is inclusive of the CFS (CFS0.6 in this experiment) used to keep the cable slightly taut.

The other characteristics of the actuator are as follows:

Weight: $12.3kg$

Dimensions: $53.7X17.1X12.9cm$

Stage 1 actuation speed: $2.21ms^{-1}$ or $120.83ms$ for $267.4cm$ stroke for no load

Stage 2 actuation speed: $3.07ms^{-1}$ or $91.67ms$ for $281.4cm$ stroke for no load

Measurement of the speed is done on an iPhone 7 using it's $240fps$ slow motion video camera. The number of frames it takes from release to static is used to calculate the speed of the actuator when there is no load on the rope output. The current configuration of 5 $2.4kg$ CFS gives us a power to weight ratio of about $33W/kg$. However, when we configure the actuator to use 5 $7kg$ CFS, it will give a power to weight ratio of about $61.8W/kg$.

5.4.4 Limitations

Given the weight and size of the actuator, it is currently not wearable. Therefore, it is mounted on a movable platform that follows the subject around(FIMP from Section 6.2.2, Figure 5.11). The platform allows the actuator to be validated as a component of the fall intervention exosuit before it is miniaturised.

Figure 5.11: A picture of FIMP with the actuator mounted on one of the arm of the fall inducing movable platform.

5.5 Subject-Actuator Interface

The output of the actuator from the rope is attached to a wire rope that passes through a Bowden cable assembly before terminating at the anchor points on the base-suit worn by the subject (Figures 5.12 and 7.2). The wire rope is first attached to the actuator's rope output via circular loops. Subsequently, the wire rope runs through 2 bearings till the start of the Bowden sheath. This allows the Bowden sheath to be pointing straight to the subject's back, improving the transmission efficiency. Finally, the Bowden cable sheath runs through the anchor points situated at the S1 spinal position and terminates at the T5 spinal position. This arrangement allows the subject to move freely around a small region while not being pulled back

Figure 5.12: Interface between actuator and subject. The output from the actuator (red line) is routed through 2 roller bearings to enter the Bowden sheath (black line). The Bowden sheath terminates at the seat harness, allowing the remaining wire rope to attach to the torso harness.

towards the metal frame of FIMP when the actuator activates. As the actuator activates, the distance between the 2 anchor points shortens, creating torso extension.

The circuit diagrams of the integrated exosuit with the actuator and fall detection system are shown in Appendix J.

5.6 Chapter Conclusion

An actuator that can partially fulfil the requirements of the exosuit has been developed. This actuator can assist when necessary, while remaining transparent to its user when inactivated. Furthermore, the actuator has a high bandwidth ($3ms^{-1}$), high force ($184N$) and large stroke ($550cm$) to provide sufficient assistive force during a fall. The actuator can be customised to alter its stroke and force output by changing the electromagnets position and the number of springs and spring constant respectively. The dual stroke design of the actuator provides a simple way to first reduce system compliance before applying the rest of the bulk force to actual work done. The usage of cam cleats allows for the decoupling of the force generating components from the user, allowing for high transparency. The user will only feel the small tug from the 0.6kg CFS when the actuator is not activated. However, the

weight and size of the actuator are currently not suitable to be worn as a wearable.

The integrated performance of the entire exosuit will be discussed in Chapter 7.

5.7 Future Work

The main limitation of the current actuator is its large size and weight, but that is necessary for the customisability of the first prototype. The next design after the exosuit validation should reduce the majority of its customisability to miniaturise and lighten the actuator. A tension or force sensor should also be placed in series with the anchor points on the subjects to determine the transmission efficiency of the actuator.

Chapter 6

Fall Inducing Movable Platform

A fall inducing system allows for the study of balance and also balance recovery. It also contributes to fall repeatability, allowing investigators to perform studies while reducing the risks of confounding variables from impeding the significance of the outcome. As mentioned in Section 2.7.1, overground walking is more desirable than treadmill if the natural dynamics of fall critical. Moreover, it is complicated to predict the stopping dynamics of the subject and adjust the treadmill to react as if the subject is moving across a stable ground. In other words, it is difficult to predict at what velocity and pressure the recovery leg will strike the treadmill. It is also unknown how fast the treadmill should slow down to prevent unwanted dynamics from being induced in the body.

The method of fall induction also plays an important part in replicating true fall dynamics. For trips and slips, it is important to direct the induction forces as close to the ankle or sole to replicate real-world falls. Hence, this study is focused on creating a Fall Inducing Movable Platform that meets the following requirement:

- Allows the subject to perform overground walking
- Does not limit the subject's speed
- Induces falls via the lower limbs

The proposed solution that meets the above requirements is a Fall Inducing Movable Platform (FIMP) that follows the subject around while determining the correct gait phase to induce a fall. Since it is a movable platform, a horizontal bar can be mounted across the top of the platform to allow for the attachment of a safety harness. The components necessary to realise FIMP's function are listed below:

- Gait phase detection to induce falls are correct timing
- "Follow-me" technology to follow subject regardless of speed
- Safe, fast and realistic fall inducing mechanism

This chapter focuses on discussing the making of all the different components necessary to make FIMP, starting with gait phase detection. Subsequently, the "Follow-me" mechanism and system control are explained. Finally, the effect of FIMP on the subjects is studied and presented.

6.1 Gait Phase Identification

Gait identification provides information on the instantaneous gait phases that allow the induction of fall at any desired phases. The main challenge to any gait identification is the difficulty in identifying correct phases even when heading angle and stride pattern change occur. The next section explains the difficulty of gait phase identification in greater detail, and the subsequent sections describe the 2 methods of overcoming these difficulties.

6.1.1 Complications of gait phase detection

Mobility is important for replicating the scenarios of falls; hence, IMU is chosen to track the subject's dynamics over other sensors. Other sensors such as motion capture cameras or goniometer are not evaluated as they restrict the user's workspace and dexterity.

The most significant problem for IMU gait phase detection is due to uncertainty in determining the periodicity of gait phase. Changing gait pattern causes irregular and unpredictable flexion angle at every gait cycle (see Figure 6.1).

Firstly, the offset of the thigh's flexion angle changes according to the extent of hip flexion. Longer and broader hip flexion leads to an increase in the flexion angle's offset. This increase in offset is mainly caused by the forward leaning of the subject's torso, increasing the speed at which the body falls forward. Hence, subjects need to widen their stance anteriorly to prevent falling forward. As the subject leans backwards, the vice versa can be observed. Leaning the torso reduces the metabolic energy required to accelerate or decelerate the body to their desired speed. Therefore, this change in offset can often be associated with changing locomotion speed.

Figure 6.1: Varying magnitude of the right thigh's flexion angles across multiple gait cycles during a continuous walking recording. It can be observed that the offset of the flexion angle also changes across different time points. Offset is obtained by employing a 2nd order low-pass filter at 0.16Hz

Changing locomotion speed also causes the magnitude of peaks and troughs of the flexion angle to varies, eliminating the use of any threshold categorisation method.

The frequency of the gait cycle also changes with locomotion speed and gait pattern. Hence, frequency analysis cannot be used to calculate the phase of the gait at any point in time.

The sudden spikes caused by the impact during both ipsilateral and contralateral heel strike further complicate the problem in IMU data. The noise is also the main reason why IMUs on the shank are not used, as the output data are very susceptible to vibrations caused during touchdown. Thigh IMUs are less affected as the ankle, and knee joints absorb most of the vibrations.

Pose initialisation (Section 3.3.3) and heading angle problems (Section 3.4.1) that happen in all IMU based methods are also prevalent in this work. This leads to the search for solutions that can remove the offset of the flexion angle; scale the angle to reduce inconsistency across different gait cycles; and have little reliance on gait frequency.

A similar approach to gait phase detection has been attempted by using a least squares regression on the thigh flexion angle with cubic splines [169]. However, they limit their subjects to a treadmill, which significantly reduces the variability of their gait cycle, as their locomotion speed is largely restricted. Besides, their method of

scaling the flexion angles and velocity based on the previous gait cycle is ineffective when locomotion speed varied significantly or during changing of heading angle. Other methods of gait identification are discussed in Section 2.8.

Two methods of gait phase identification are implemented in this work. The first method is based off Quitero's work [169]. However, instead of their suggested cubic splines, only the basic bandpass filter and scaling based on previous gait cycle will be implemented. The second method is based on sine wave fitting using the Levenberg Marquardt algorithm and normalising the fitted wave to obtain even scaling among different gait cycle.

Both of the methods will implement gait phase identification on the legs individually. This provides an advantage over other algorithms that obtain gait phases using the combined kinematics of 2 legs because changes in individual gait pattern do not affect the gait phase identification. An example may be a subject with drop foot syndrome. The affected leg has drastically different kinematics than the healthy leg. However, because the current method identifies the gait phases individually, the identified gait phases can differ significantly between each leg and still function reliably.

6.1.2 Experiment Setup

All trials have approved by the NTU Institutional Review Board (IRB-2018-08-006). The gait phase identification of this study relies on IMUs placed on the subject's torso and left thigh only. No IMUs were placed on the shank for gait phase identification (see explanation in Section 6.1.1). The IMUs were obtained from *Yost Labs*, and they were connected to a central micro-controller (Raspberry Pi 3) using a USB hub. A mean sampling rate of 333Hz was obtained after using *Yost Labs* proprietary Q-Comp filter. Each sample for gait identification consists of the quaternion orientation output and angular velocity of the torso and thigh IMUs.

A total of 3 subjects were recruited for this experiment. They were 2 males and 1 female, with an average age of 28 ± 2.45 years, average height of 171.67 ± 6.94 cm, average weight of 68.33 ± 5.31 kg, and an average BMI of 23.19 ± 1.27 . All of them have no history of locomotor impairment, neurological impairment or cardiovascular diseases. Each subject was asked to perform 3 types of walking trials:

1. Walking along a designated pathway with 90 deg and 180 deg in both left and right direction
2. Walking in a straight path in alternating fast and slow speed

3. Walking in a figure of eight paths with a turning radius of approximately 1.3m

These motion were chosen as they represent all the different kinds of gait motion such as (1) changing heading angle, (2) changing gait speed, (3) making sharp turns and (4) gait initiation/termination.

Pose initialization and Heading angle

Pose initialization can be solved by using the same method as Section 3.3.3.

$$Q^i = \overline{Q_{init}^i} * Q_{raw}^i \quad (6.1)$$

where Q_{raw}^i is the i^{th} body raw quaternion obtained from the IMU, $\overline{Q_{init}^i}$ is the i^{th} body raw conjugate quaternion at initial pose, Q^i is the reoriented quaternion from the initial pose and $*$ is the Hamilton product (see Section 3.3.3 for more explanation). The resulting quaternion will rotate from the initial IMU position.

The problem of changing heading angle is also solved in the same way as Section 3.4.1. After obtaining the heading angle from the torso IMU, joints flexion/extension movements can be reoriented into the global sagittal plane via Equation 6.2.

$$Q_{ro}^i = Q_{\psi} * Q^i \quad (6.2)$$

where Q^i is the i^{th} body quaternion obtained in Equation 3.36, and Q_{ro}^i is the inverse heading quaternion obtained from above.

6.1.3 Bandpass Filtering

The basis of this method depends on a bandpass filter to remove the offset and reduce the effect of noise caused by the impact due to foot touchdown. The filter is implemented on both the thigh's flexion angle and flexion velocity. The thigh is used because it can capture the pattern of gait while having a less noise than other lower limbs. Subsequently, the filtered flexion angle is scaled to match the maximum and minimum flexion velocity of the previous gait cycle. Lastly, the inverse tangent is used to obtain the phase angle between the flexion angle and flexion velocity.

The bandpass filter is a second-order band-pass Butterworth filter with low pass and high pass cut-off at 3Hz and 0.4Hz respectively. The flexion angle is extracted from the processed IMU quaternion ($Q^{i,local}$), using the method described in Appendix A, with a YXZ rotation order. The flexion velocity is directly obtained from the x-axis gyroscope. Filtering introduced a slight phase shift (60ms) on the data,

but it is insignificant as compared to the average 1-second gait cycle interval (Figure 6.2). Table 6.1 shows the average values of the flexion angle and velocity before and after filtering. A decrease in average, and standard deviation values signify that the offset has been decreased.

Table 6.1: Average angle and velocity values before and after filtering

Data	Before Filtering		After Filtering	
	Average	Std Dev	Average	Std Dev
Flexion Angle	-3.43×10^{-2}	0.226	-7.07×10^{-5}	0.138
Flexion Velocity	-4.21×10^{-3}	1.785	-7.69×10^{-7}	1.394

The filtered flexion angle and velocity form the phase variables that are used to calculate the phase angle at the next section.

Figure 6.2: Bandpass filter (yellow, solid) and Spline fitted curve (orange, dotted) curve as compared to raw IMU flexion angle (blue, dash). Spline fitting as suggested by Quintero [169] is implemented to highlight the difference in offset variability with bandpass filter. With the bandpass filter, the offset can be removed.

Scaling of Phase Variables

Phase angle(Φ) is used as an intermediate variable to determine the different gait phases. It is computed based on the inverse tangent function (atan2) by dividing flexion angle (θ_{torso}) over flexion velocity ($\dot{\theta}_{torso}$). However, the magnitude of the 2 axes ($\theta_{torso}, \dot{\theta}_{torso}$) varies when gait pattern changes, even after filtering. Hence, a method similar to Quintero et al. [169] is used to scale the flexion angle axis to

match the flexion velocity, ensuring a more consistent phase angle calculation. This method is abbreviated as VMS.

$$\theta_{torso}^- = \kappa(\theta_{torso}) \quad (6.3)$$

where θ is the flexion angle; $\bar{\theta}$ is the scaled flexion angle; κ is a scaling factor and it is calculated by using the max and min of the previous gait cycle:

$$\kappa = \left| \frac{\dot{\theta}_{torsomax} - \dot{\theta}_{torsomin}}{\theta_{torsomax} - \theta_{torsomin}} \right| \quad (6.4)$$

$$(6.5)$$

where $\dot{\theta}_{torso}$ is the filtered angular velocity from the gyroscope; $\dot{\theta}_{torsomax}$ and $\dot{\theta}_{torsomin}$ are the maximum and minimum filtered angular velocity of the previous gait cycle; $\theta_{torsomax}$ and $\theta_{torsomin}$ are the maximum and minimum filtered flexion angle of the previous gait cycle.

A full gait cycle is determined by detecting the negative to positive zero crossing of the flexion velocity ($\dot{\theta}_{torso}$). The phase angle is then calculated as follows:

$$\Phi = \tan^{-1}(\bar{\theta}/\dot{\theta}) \quad (6.6)$$

The inverse tangent is computed using the *atan2* function in c++.

However, when the subject is not moving, there should be no scaling involved as there is no gait at all. This is easily implemented by setting a boundary on flexion velocity and angle to detect gait initiation. Arbitrary values of $0.025rad/s$ and $0.025rad$ were chosen as the threshold for flexion velocity and angle respectively:

$$\Phi = \begin{cases} 0 & , \text{ if } \dot{\theta}_{torso} < 0.05 \text{ \& } \theta_{torso} < 0.05 \\ \tan^{-1}(\theta_{torso}^-/\dot{\theta}_{torso}) & , \text{ otherwise} \end{cases} \quad (6.7)$$

If a subject stops midway of a gait, his/her thigh flexion angle is non-zero. However, because of the bandpass filter, the constant flexion angle is removed, allowing for the gait phase angle to be recalculated from zero again.

Figure 6.3 shows a flowchart that describes the bandpass filter and velocity matching scaling factor.

Figure 6.3: Data flow and conditions when using bandpass filter with velocity matching scaling factor (VMS). The final output is obtained by evaluating the sine wave at the last timestamp of the fitted input samples.

6.1.4 Sine-Wave fitting

A limitation with the previous method of bandpass filtering with scaling is the inconsistency of the peaks of each gait cycle as the subject walks with different gait pattern. For example, a short stride followed by a long stride leads to a significant increase in the scaling factor (κ) of the VMS, creating a discrete jump in the subsequent gait cycle. Hence, the bandpass filter is only suitable for walking with consistent speed. This section explains how this limitation can be overcome by fitting a standard sine wave over the window of data.

This method of sine wave fitting starts with using the same bandpass filter as the previous method to remove the offset of the flexion and velocity signal. After that, a sine wave is fitted over the filtered data using the LMA, a non-linear optimisation technique. The flexion angle and velocity signals are fitted separately using LMA, and the phase angle is obtained by using the Equation 6.6 with the fitted flexion angle and velocity.

The sine wave is formed using Equation 6.8.

$$F_s(t) = A_s \sin(f_s(t + \phi)) - B_s \quad (6.8)$$

Where A_s is the magnitude of the sine wave, f_s is the frequency, t is the sample count or timestamp, ϕ is the phase angle of the sine wave, and B_s is the offset. In the current application, only the frequency (f_s) and phase angle (ϕ) are variables. The magnitude (A_s) is fixed at one, causing the fitted wave to have consistent peaks even

when the gait pattern changes. The offset (B_s) of the sine wave is set to zero because it is assumed that the bandpass filtered data has already had its offset removed.

Levenberg Marquardt Algorithm

Levenberg Marquardt Algorithm (LMA) is used to fit a sample of the data to a sine wave. LMA is an iterative, non-linear, least square, curve fitting algorithm, and it interpolates between the Gauss-Newton Algorithm (GNA) and gradient descent. Individually, GNA and gradient descent can both function as a non-linear optimisation algorithm. GNA is fast and suitable for problems with quadratic functions, but it quickly converges to saddle points or even fail if its Hessian matrix is ill-conditioned. On the other hand, gradient descent is slow but it works in a large variety of situations. Combining GNA and gradient descent as LMA allows faster convergence even when the fitting function is chaotic and confusing.

Before any fitting can occur, the residual (error) equation must first be defined. Equation 6.9 describes the least square function to fit a sine wave to a window of empirical data.

$$S(\Lambda, \mathbf{X}) = \sum_{i=1}^n (y_i - F(\Lambda, x_i))^2 = Q(\Lambda, \mathbf{X}, \mathbf{Y})^T Q(\Lambda, \mathbf{X}, \mathbf{Y}) \quad (6.9)$$

where Λ is the vector of parameters (f_s, ϕ) for the sine wave, y_i and x_i are the x and y-axes empirical data, and $F(x_i, \Lambda)$ is the sine wave function evaluated using Λ parameters with x_i input. $Q(\Lambda, \mathbf{X}, \mathbf{Y})$ is a vector formed by $(y_i - F(\Lambda, x_i))$ for all i .

Next, the GNA method of LMA is described as differential of Equation 6.9 with respect to the linear approximation of $S(\Lambda, \mathbf{X})$. For a small change in Λ , $S(\Lambda + \sigma_\Delta, \mathbf{X}) \approx S(\Lambda, \mathbf{X}) + J\sigma_\Delta$:

$$x_{i+1} = x_i - J^{-1}Q(\Lambda, \mathbf{X}, \mathbf{Y}) \quad (6.10)$$

where J^{-1} is the inverse Jacobian of the function $Q(\Lambda, \mathbf{X}, \mathbf{Y})$. When J is not a square matrix, inverse Jacobian (J^{-1}) is written as the pseudo inverse matrix $((J^T J)^{-1} J^T)$, giving:

$$\sigma_\Delta = x_i - x_{i+1} = (J^T J)^{-1} J^T Q(\Lambda, \mathbf{X}, \mathbf{Y}) \quad (6.11)$$

where σ_Δ is the step change (identical to $x_i - x_{i+1}$).

Gradient Descent functions similarly to GNA, but it uses a different definition of the step change (σ_Δ):

$$\sigma_\Delta = \gamma_\delta J_s \quad (6.12)$$

where γ_δ is a varying step size, and J_s is the Jacobian of the function $S(\Lambda, x)$

Finally, LMA combines GNA and gradient descent as (6.13):

$$\sigma_\Delta = (J^T J + \lambda_\delta)^{-1} J^T Q(\Lambda, \mathbf{X}, \mathbf{Y}) \quad (6.13)$$

where λ_δ is a non-negative damping factor that brings (6.13) towards a gradient descent algorithm or a GNA. When the reduction of $S(\Lambda)$ is big, λ_δ is set small, and (6.13) behaves like GNA in (6.11). Conversely, when reduction of $S(\Lambda)$ is small, λ is set big, and (6.13) behaves like gradient descent in (6.12). This is because the Jacobian of the least square equation (J_s) is:

$$J_s = \frac{\partial S(\Lambda, \mathbf{X})}{\partial \Lambda} = -2(J^T Q(\Lambda, \mathbf{X}, \mathbf{Y}))^T$$

when λ is big, the inverse term of Equation 6.13 becomes like a constant, representing γ in Equation 6.12. Therefore, the step size will be taken in the general direction of the gradient.

A flowchart depicting the process of filtering and fitting the raw flexion angle and angular velocity is shown in Figure 6.4. The flexion angle and flexion angular velocity both go through the same process. The final gait phase angle (Φ) is obtained by the inverse tangent of flexion velocity over the flexion angle (Equation 6.6).

Several factors and conditions contribute to the accuracy of the gait phase detection using LMA are listed below, with the parameters used in this study within the brackets:

Window Size (150): The number of samples used to fit the sine wave affects the smoothness of the output data point. A shorter window leads to noisier output, but a longer window is slower to process

Maximum Frequency Change (0.1): As each gait cycle consists of fast and slow movement, it causes the frequency of the sine wave to vary slightly, but there should not be a sudden change. Hence, this parameter checks if there is a sudden change in frequency, and refit the data with a lower tolerance to better match the frequency of the previous iteration. Increasing this value leads to noisier data while decreasing this value leads to inaccurate fitting.

Figure 6.4: Data flow and conditions when using Levenberg Marquardt algorithm. The final output is obtained by evaluating the sine wave at the last timestamp of the fitted input samples.

Minimum Frequency (0.1): During the transition between stopping and walking, the condition of *maximum frequency change* prevents the sine wave from changing too fast, leading to abnormally low frequency. Hence, this condition allows for a slow starting gait cycle to be refitted from the initial guess. Decreasing this value decreases the rate at which slow starting gait is detected, but increasing it causes more noise in the normal gait phase. Note that this frequency represents gait cycle per second, which translates to about 1 full gait cycle every 10 seconds.

Initial Guess ($f_s = 0.016$, $\phi = 91$): A good initial guess reduces the number of LMA iterations and increases the speed of optimisation drastically.

Tolerance (normal tol=0.01, reduced tol=0.1): The tolerance controls how accurately to fit the sine wave to the filtered data. This value controls the speed, as well as the accuracy of the gait phase detection.

Movement Criterion (velocity < 0.025, flexion < 0.025): When the subject stops moving, the small oscillations of a standing person should not be categorised as a gait phase. Hence, this criterion is used to classify static movements

as standing still and not calculate these gait phases. Increasing these values causes slower parts of a gait cycle to be classified as stationary, while decreasing these values lead to small oscillations to be classified as gait phases.

The Eigen linear algebra library [181] is used to implement the Levenberg Marquardt Algorithm.

6.1.5 Gait Identification Results

The results of the extracted phase angle (Φ) are presented in Figure 6.5 for VMS (Section 6.1.3) and Figure 6.6 for LMA fitted data (Section 6.1.4).

Figure 6.5: Combined Mean and standard deviation of Phase angle obtained using a bandpass filter, and a velocity matched scaling factor. The data is of a subject's walking gait while he walks at normal, fast and slow speed. The solid blue line is the mean of the extracted gait phase, and the shaded area is the limits of the standard deviation.

Both methods performed reliably when the gait speeds were relatively consistent with their average walking speed. The maximum standard deviation of VMS is 8.86%, and that of LMA is 11.91%. The dip at the end of the gait phase occurred when the subject was restarting a new gait cycle. The slight indentation in VMS at 40% of the gait cycle may have caused a slightly less accurate gait phase output. A more linearly distributed gait phase across the gait cycle would allow better separation of the phase angle at different gait cycles.

On the other hand, VMS performed much faster with its more straightforward computation. It achieved an average of 0.00963 ms per sample, while LMA required

Figure 6.6: Combined Mean and standard deviation of Phase angle obtained using bandpass filter and LMA curve fitting. The data is of a subject's walking gait while he walks at normal, fast and slow speed. The solid blue line is the mean of the extracted gait phase, and the shaded area is the limits of the standard deviation.

0.719 ms per sample. Nonetheless, both methods proved to be much faster than the IMU's sampling rate of 3 ms per sample, and hence, suitable for real-time implementation.

The results of the extracted phase angle (Φ) for a normal walking speed is shown in Figure 6.7. It can be observed that the computed phase angles are repetitive for both methods.

Figure 6.7: Phase angle for a section of a normal speed walking gait. Both VMS and LMA methods perform reliably for a consistent walking speed

Different gait speed

When comparing the gait phases to different walking speed, both methods can faithfully obtain the phase angle while adjusting to the different gait cycle period (see Figure 6.8 and Figure 6.9).

Figure 6.8: VMS Phase angle for different walking speed. Each walking speed has a different period as seen by the repeating gait cycle.

Figure 6.9: LMA Phase angle for different walking speed. Each walking speed has a different period as seen by the repeating gait cycle.

Even when subjects rapidly changed their gait speed, both methods managed to identify the gait phase. Figure 6.10 shows the subject walking 4 slow strides and 4 fast strides repeatedly.

Figure 6.10: Gait phase for subject changing between slow and fast speed. Both VMS and LMA can detect the gait phase reliably. The green dotted boxes highlight the incapability of VMS to maintain a repetitive phase angle profile when there is a large change in gait speed.

Both VMS and LMA can convert the flexion angles and velocity to correct gait phase even at rapidly changing gait speeds. However, at the transition from slow and fast speed (green dotted boxes in Figure 6.10), VMS has difficulty maintaining a constant phase angle peak. This is due to VMS relying on the velocity peaks of the previous gait cycle to adjust its scaling factor.

Change of heading

During the sharp change of heading (sharp turn 90 degrees), there is a significant change in the flexion angle of the subject. The extracted phase angle tends to drop suddenly to zero before rising again. However, this phenomenon is less obvious in LMA than in VMS (Figure 6.11). Additionally, the phase angle returns to the normal range and period after 1 gait cycle for LMA and 2 to 3 gait cycles for VMS.

When subjects are doing gentle turns, both methods can extract the phase angle accurately (Figure 6.12). This is tested by asking subjects to perform walking at their normal speed along with a figure of eight path. The turning radius of the figure of 8 is approximately 1.3m.

Gait initiation and termination

As mentioned above, the scaling multiplier (κ) affects the phase angle even when the subject is stationary. Hence, a threshold of $0.025rad/s$ and $0.025rad$ were chosen

Figure 6.11: Phase angle for a 90 degree change in heading at different walking speed (indicated by the dotted green box). There are reduction in the extracted phase angle, but they recover to normal range after 2 to 3 gait cycles.

to separate standing from walking for flexion velocity and angle respectively, before the phase angle can be computed. The results are shown in Figure 6.13. It can be observed that even when subjects are initiation or terminating their gait, the phase angle can be extracted without much noise.

Figure 6.12: Extracted phase angle of subjects walking along the curvature of a figure of 8 path. Both VMS and LMA are able to extract a periodic phase angle pattern.

Figure 6.13: Phase angle for gait initiation (top) and termination (bottom).

6.2 Trip and Slip Mechanical System

Although only the trip mechanism is necessary for this project, a slip mechanism is also included in this section as it is necessary for future work.

6.2.1 Follow-me FIMP

Due to the differences in overground and treadmill walking, a true overground solution is necessary to capture the real fall dynamics. Also, most ceiling-mounted railings for safety harnesses have noticeable inertia that causes the subjects to feel a tug on their body every time they change their gait speed. A motorised auto-following machine allows overground walking and eliminate the inertia from the ceiling mounted railings.

Previous iterations of FIMP require an investigator to push it along the back of the subject and stop FIMP at the same instant when the perturbation from the motor and brake is initiated. However, the synchronisation between the investigator and the perturbation system is often wrong, leading to varying degrees of fall severity. Hence, FIMP is being motorised with wheels along the central axis to allow for perfect synchronisation of the perturbation system and the movement of the platform.

Two motorised wheels were mounted along the central axis of FIMP such that the wheels can rotate FIMP around with zero turning radius. The DC motors obtained from *Motion Tech Motor* have a power rating of 250W, and were equipped with electromagnetic brakes. They were controlled via a Sabertooth 2x32 motor driver. The driver was configured in mixed mode, which accepted 2 inputs; one input signal that controlled the forward speed, and another input signal that controlled the turning speed.

Intel Realsense Depth Camera D435 was used to estimate the position of the subject within FIMP. Usage of the depth camera allowed for subject tracking without any physical contact, eliminating interference with normal walking gait. The camera was mounted at the back of FIMP, pointing directly forward at the centre of FIMP (Figure 6.14). The estimated distance of the subject can be obtained by averaging all the depth pixels of the camera. An estimated distance of 60 cm was maintained with the use of a Proportional Derivative (PD) controller. The output of the PD controller then entered into a motor driver controlling the forward speed of the motorised wheels.

As the subject turns, he/she will no longer be centred within the camera. Hence, the angle of the 2 vectors (subject's average pixel centre to camera, and FIMP's

forward axis) will be used as input to another PD controller (Figure 6.15). The output of this PD controller controls the differential speed of two wheels via a motor driver.

Figure 6.14: Calculation of forward distance for the subject follower algorithm.

Figure 6.15: Calculation of orientation angle for the subject follower algorithm.

6.2.2 FIMP Mechanical Design

Falls are induced via cables attached to the ankle of the subject. The continuous movement of the legs during gait requires the cables to be freely moving. When pulled, these cables do not immediately cause a fall as it needs to reel in the excess cables. This delay in force transfer contributes to variability in the fall recovery motion and creates the risk of uncontrolled tripping over the slack cables. The problem is averted by using power springs obtained from readily available measuring tapes. The power springs (return springs) from the measuring tapes are attached to the cables tied to the subject's ankle, ensuring that the cables are always slightly taut.

A rendition of the setup is shown in Figure 6.16. A trip was induced via an electromagnetic brake connected to the ankle via a power spring. The brake was purchased from *SINFONIA* (ERS-260L) with 8Nm static friction torque (Figure 6.17). On the other hand, a slip was induced via a DC motor because the sudden acceleration of stance leg necessary for slip could only be possible with a pull. The DC motor was obtained from *XaJong Co. Ltd* (M35SWG-2436), with continuous torque of 1Nm and speed of 3600rpm (Figure 6.18). A wrap spring clutch from *Tiny-Clutch / Helander Product, Inc* was then attached to the DC motor output to disengage the inertia of the DC motor from the power spring. The clutch can be engaged with 0.12Nm of torque, reeling in the cable that is mounted on the exterior shell of the power spring. A 24V, 35AH Lipo battery powered the entire system. The circuit used for activating the trip brakes and slip motors are described in Appendix E.

This mechanical setup was subsequently mounted on a platform made from 40mm X 40mm aluminium extrusion. The DC motor for slip was mounted on the front of the platform, while the trip's brake was at the back. The internal walking area is 175cm X 115cm, with 208cm of vertical space. The tension experienced from the power springs during non-excitation are as indicated in Table 6.2 (measured using the force sensor mentioned in Appendix G.5).

Table 6.2: Tension force on the cable for both the trip power spring (front) and the slip power spring (back)

	Trip Spring	Slip Spring
Static Force (N)	3.0	1.0
Dynamic Force (N)	5.9	3.5

The ideal trip and slip system should not resist the movement of the ankle until a fall is induced. However, the current trip and slip systems, when utilised alone, re-

Figure 6.16: The mechanical setup of FIMP. Brake is used for trips induction and DC motor for slips. Slips and trips are induced on the left leg via wire rope (green dotted circle). The structure is made from 40cm X 40cm aluminium profiles.

quire $5.9N$ and $3.5N$ of force respectively to move the ankle. When subjects utilise the trip and slip system together, the user only feels $2.4N$ of resistance when swinging the ankle forward. This is due to the combined forward (slip) and backward (trip) forces that eliminate each other. This combined force is barely noticeable by the subjects, implying that FIMP is transparent to the user during normal gait (Section 6.3.2).

When the trip brake activates, subjects experience a maximum of $350N$ resisting force on the swinging motion of the ankle, which is sufficient to induce a trip recovery response (Table 6.3). Similarly, the slip motor pulls the ankle forward with $110N$ of force, leading to a slip recovery response.

Table 6.3: Maximum tension on the cable from DC motor and brake

	Trip Brake	Slip Motor
Max Force(N)	347.8	110.3
ON Duration (ms)	250	750

Figure 6.17: The brake mounted on FIMP with a concentric rod keeping the constant force spring centred.

Figure 6.18: The motor is mounted horizontally with its output shaft connected to a bi-directional clutch and finally to a constant force spring. To prevent over-reeling of the motor, a thick acrylic sheet with a hole prevents the cable endings from being reeled in. In addition, a fuse is used in series with the motor to prevent large static torque.

When conducting slip trials, the subject's walking pathway is covered with 2 layers of sliding sheet. The coefficient of friction between the 2 layers of sliding sheet is approximately 0.15 for both static and kinetic scenarios. This inclusion of sliding sheets replicates the true slip conditions, whereby the slip foot continues to slide forward even after the initial pull by the slip motor. Floors that are coated with

slippery solutions also allow for the real slip condition to be replicated [197–199]. However, these experiments commonly depend on ceiling hoist for safety harness because the slippery surface is difficult to control and constraint. This causes the subject to feel the inertia of ceiling hoist and thereby, reducing the genuineness of the slip. Other methods of inducing a slip rely on a split-belt treadmill or sliding flat plate [13, 200, 201]. However, it only allows slipping for a short distance, often at a controlled speed which does not mimic a true slip. When the treadmill stops to allow the user to recover, the user regains stable contact with the treadmill belt which further improves their stability which is not seen in true slip.

Fall severity

Fall severity depends on multiple factors, some of which can be controlled via the system (see Table 6.4).

Table 6.4: Factors affecting fall severity

Factors	Controllable?	Direction for higher Trip severity	Direction for higher Slip severity
Gait speed	No	increase	increase
Torso lean angle	No	increase	decrease
Floor/sole friction	No	-	decrease
Actuator On duration	Yes	increase	increase
Gait Phase	Yes	varies	varies

Gait speed relates to the amount of momentum in all the body parts. However, gait speed cannot be easily controlled except on a treadmill. Consequently, experiments with FIMP rely on the subjects capability to maintain constant gait speed.

The lean angle of the torso (flexion angle) affects the position of the CoM in the BOS. Trip causes CoM to shift anteriorly; hence, an extended torso posture is useful for reducing trip severity. On the contrary, slip causes the CoM to shift posteriorly; hence, a flexed torso posture is good at reducing slip severity. Since this factor is subject dependent, it is uncontrollable via the FIMP system. In an experiment with multiple falls, subjects inevitably adopt a position that better reduces their fall severity.

Friction between the floor and shoe significantly affects the severity for slip as it directly affects the speed at which the anterior foot is separated from the contralateral foot with any given duration. Friction on the floor is determined by 2 main factors: (1) Pressure on the floor exerted by the user and (2) the friction coefficient

between the shoe and the floor. Pressure on the floor can be controlled by adopting a lower stance, which also decreases the swing phase duration. The friction between the shoe and floor can also be adjusted by requesting subjects to wear low friction shoes and making the floor slippery.

The ON duration is the timing that the DC motor and brake are switched on. Adjusting the ON duration affects the slip severity more significantly than the trip. This is because a trip requires a sudden arrest of the ankle, and increasing the timing only increases the duration of zero velocity. On the other hand, because slip is simulated via a sudden jerk at the end of the swing phase, increasing the ON duration separates lower limbs further. This leads to the CoM being at a greater distance from the centre of the BoS. For this study, trip ON duration is chosen arbitrarily as long as they can produce a fall reaction, but slip duration has to be adjusted with every change in environment and individual.

Lastly, the gait phase controls the recovery strategy and the time available for the subject to adopt the correct strategy. For example, arresting the leg at mid-swing instead of early swing for a trip leads to a higher trip severity as the body is at a less stable stance.

6.2.3 System Control

Integration of the system is as shown in Figure 6.19. The subject follower ("Follow-me" mechanism) ensures that the platform follows the subject around. Upon a trigger of a button, the gait phase identification process starts on the micro-controller within the Exosuit. Since the gait phase is an analogue value, it is separated into 20 equal segments from $-\pi$ to π . Once the gait phase has entered the pre-selected segment for the corresponding induced fall, the fall mechanism activates. An emergency stop button is wired between the 35AH Lipo battery and the DC motors and brakes.

Synchronising the fall mechanism to the gait phase has been a problem of previous works. A solution is achieved by making use of the gait phase detection algorithm to calculate the phase angle (Section 6.1). For induction of trips, the gait phase of the early swing is used for generating elevating strategy and late swing for lowering strategy. For slips, perturbation is given at the early stance phase, when the foot has just touchdown.

During an experiment, the FIMP platform automatically follows behind the subject. An investigator following the moving platform will randomly push a corre-

Figure 6.19: System control of FIMP. Subject starts walking in FIMP. RealSense camera detects the user's position and drive the wheels to follow the subject. As FIMP follows, it polls for investigator trigger via a button pressed for intention to trip the subject. When the button is pressed, the system automatically initiates the gait phase detection algorithm. Upon the correctly detected gait phase, the system immediately stops the wheels of FIMP and activates the trip brake. Subjects were instructed to recover and stand straight after the trip.

sponding button to activate gait detection for inducing falls. The system will then automatically induce trip or slip when the correct gait phase is detected; fall is not induced at the instance of the button pressed. The investigator must push the button again to induce another fall.

The circuit diagrams of the integrated system with exosuit's actuator and fall detection system are shown in Appendix J.

6.3 FIMP Evaluation

The FIMP platform aims to perturb the subjects at the correct gait phase under the direction of the investigator. Ideally, FIMP should not affect the subjects in any way when a perturbation is not being induced. In this section, the transparency of FIMP is evaluated, followed by the effect of the trip mechanism.

6.3.1 Experiment Setup

All trials have approved by NTU institutional review board (IRB-2018-08-006). The gait phase detection system relies on IMUs placed on the subject's left thigh and torso, although other IMUs on the right thigh and shanks are also present. The IMUs were obtained from *Yost Labs*, and they were connected to a central micro-

controller (Raspberry Pi 3b+) using a USB hub. A mean sampling rate of 333Hz was obtained after using Yost Labs proprietary Q-Comp filter. Each sample for gait analysis consists of the body's local acceleration, local angular velocity and global quaternion orientation output. The entire gait phase detection system was attached to a big velcro, which was worn around the subject's waist (Fig. 6.20). The waistband was tightened to the level where it did not slide down and yet remained sufficiently loose to allow hip and lumbar flexion.

16 Qualisys Miquis M3 mocap cameras and 2 video cameras were used to track subject's motion. The cameras were configured to sample at 200Hz. 53 Markers were placed on the L/R (Left and Right) Forehead, L/R Back head, clavicle, sternum, C7, right back, T10, L/R shoulder, L/R upper arm, L/R elbow, L/R forearm, L/R dorsal tubercle of radius, L/R styloid process of ulna, L/R middle finger's metacarpophalangeal joint, L/R anterior superior iliac spine, L/R posterior superior iliac spine, L/R thigh (4 markers), L/R lateral knee epicondyle, L/R tibia (4 markers), L/R ankle medial malleolus, L/R ankle lateral malleolus, L/R heel and finally L/R middle toe metacarpophalangeal joint (Fig. 6.20).

A total of 7 subjects were recruited for this experiment. They were 2 females and 5 males with an average age of 25.33 ± 0.94 years, average height of 168.33 ± 2.36 cm, average weight of 58.33 ± 6.24 kg, and an average BMI of 20.54 ± 1.69 . All of them have no history of locomotor impairment, neurological impairment or cardiovascular diseases.

For each subject, they were asked to perform 3 types of walking trials at their preferred speed along a straight path:

- 1) **NormalWalking (NW)** : 5 trials of walking without ankle cable and harness
- 2) **StrapWalking (SW)** : 5 trials of walking with attached ankle cable and harness, but no fall
- 3) Walking with attached ankle cable and harness with random falls
 - 3.1) **MidSwing trip (MS)** : 3 trips initiated at mid-swing gait phase
 - 3.2) **EndSwing trip (ES)** : 3 trips initiated at end-swing gait phase

Ankle cable refers to the cable that is attached to the subject's ankle. This cable is kept taut by the power spring, and its force may influence the way the subject walks.

Due to the space constraint of the laboratory and motion capture volume, all the falls happen within a specified region when subjects are walking along a straight

Figure 6.20: All subjects start by wearing a base Velcro suit, then a torso and seat safety harness and finally the waistband with all the GPD hardware. The IMUs are placed on the torso, thighs and shanks of the subject, although only the left thigh IMU is used. Finally, markers are secured onto the subject via Velcro.

path. The randomness of fall and element of surprise is introduced by walking multiple trials and activating the trip only during some of the trials. An investigator constantly follows behind FIMP to activate the fall via the control switches and to press the emergency stop button should any accident happen.

The capture volume of $9m$ by $5m$ by $2m$ enables subjects to perform approximately 15 steps during normal walking. During fall trials, falls are typically induced around the 6th to 9th step, which occurs in the middle of the capture volume.

All captured data were filtered with a 6 Hz low pass frequency.

6.3.2 FIMP Transparency

To study the transparency of FIMP, there must be no differences between the NormalWalking and StrapWalking trials. Conventional methods of comparing the different trials such as maximum, minimum, standard deviation and other ways of

zero dimension analysis are not suitable in this scenario. This is because the effect of the different trials may be buried within the zero-dimensional analysis (A big magnitude change in StrapWalking flexion angles at the end-swing phase may be overshadowed by the magnitude of the mid-swing phase flexion angle). Therefore, a topological method for detecting field changes in smooth n-dimensional continua called SPM [202] is employed. Specifically, SPM allows for the analysis of sagittal plane flexion angles for different trial types at all intervals of gait cycles. SPM works by comparing datasets at all time samples and adjusting the statistical threshold (p-value) to account for the variability of the data. The higher the variability of the data, the larger the adjusted p-value. Hence, two datasets with high variability require a breach at a high threshold to be classified as statistically different.

The gait cycle of every trial is segmented by heel strike. Every gait cycle is also normalized for fixed stance and swing phase duration. The first 60% of the gait cycle is allocated to the stance phase and the remaining 40% for the swing phase. The toe-off of each leg is used to demarcate the end of stance phase. The flexion angle of hip, knee and ankle joints between NormalWalking and StrapWalking trials are compared to quantify the transparency of FIMP.

Figure 6.21 and 6.22 show the SPM results for statistical differences between NormalWalking and StrapWalking. A two sample t-test was conducted, with a chosen p-value threshold of 0.05. The individual subject's FIMP analysis for their left and right legs are shown in Appendix K.

Left Leg

Results indicated that there was little to no differences between the hip and knee flexion of the left leg between NormalWalking and StrapWalking (Figure 6.21). This implies that the ankle straps did not affect the movement of the thigh and shank. On the contrary, there are significant differences in the ankle flexion angles for the left leg (with attached straps) during the swing phase. However, the effect is not consistent among all the subjects, indicating that certain subjects are more susceptible to the influence of the ankle straps. Several factors may contribute to the difference in ankle flexion. Firstly, the act of attaching the ankle straps requires interaction with the reflective markers on the ankle. The attached straps may also affect the alignment of the markers with the shank malleolus during the plantar/dorsiflexion that happens during swing phase. Therefore, the ankle strap may have been the cause of the difference between NormalWalking and StrapWalking. However, the

effect of the power springs that keep the trip and slip mechanism taut must not be ignored. The tension force on the wire rope may have reduced the ease of achieving the subject's normal toe clearance height, leading to an increase in dorsiflexion for extra toe clearance. Additionally, the tightness of the straps may have prevented the normal execution of dorsiflexion. Hence, more experiments have to be conducted to determine the actual cause of the difference. Future experiments can be improved by reducing the force of the power spring and controlling the tightness of the ankle straps.

Right Leg

The right leg that did not have any strap attached showed no significant difference between NormalWalking and StrapWalking trials for all lower limb joints (Figure 6.22).

These results indicated that FIMP can provide a reasonable amount of transparency to the subjects. The only drawback is the induction of larger dorsiflexion for toe-clearance during the mid-swing phase for 4 out of 7 subjects. This is caused by the ankle straps and the tension on the wire ropes attached to the ankle and fall inducing mechanisms. However, this larger dorsiflexion has minimal effect on balance recovery during a fall. This is because the excess dorsiflexion happens during mid-swing, which does not generate any appreciable forces or torque experience on the subject. The only effect may be a slight increase in fatigue on the muscles responsible for dorsiflexion (e.g. tibialis anterior).

Gait Parameters

The gait parameters (stride length and stride duration) of the 7 subjects for both legs are shown in Table 6.5. When comparing the Coefficient of Variation (CV) of each subject between NormalWalking and StrapWalking, a maximum difference of 0.07 (7%) is observed for stride length, while a 0.02 (2%) difference is found for stride duration. These magnitudes are very small and are within the variability of a single subject [203]. Therefore, it further validates the result found from the SPM analysis that the trip mechanism in its inactive state does not affect the gait parameters significantly. CV is often used to compare gait parameters to account for individual differences such as leg length and walking speed.

Left Leg Normal vs Strap Walking Two Sample t-test

Figure 6.21: Comparison of NormalWalking (NW) vs StrapWalking (SW) trials for the left leg using SPM. The left leg is the leg with the ankle strap attached for fall induction. Top row indicates the mean hip, knee and ankle flexion angles for all subjects and standard deviation clouds; mean ($\pm$ std.dev). Second row indicates the Two-sample t-test on the data in top row. Third row shows a colour map highlighting significant differences of the t-test result in second row. The last row shows the significant different effect size of individuals. Significant differences are seen in the ankle joint during the mid-swing phase for the majority of the subjects. There are also differences found in the knee during the mid-swing phase, but it is less consistent among all the subjects.

Right Leg Normal vs Strap Walking Two Sample t-test

Figure 6.22: Comparison of NormalWalking (NW) vs StrapWalking (SW) trials for the right leg using SPM. The right leg is not attached to any ankle straps. Top row indicates the mean hip, knee and ankle flexion angles for all subjects and standard deviation clouds; mean ($\pm$ st.dev). Second row indicates the Two-sample t-test on the data in top row. Third row shows a colour map highlighting significant differences of the t-test result in second row. The last row shows the significant different effect size of individuals. No significant differences are found in any of the joints for the majority of the subjects

Table 6.5: Gait parameters between NormalWalking and StrapWalking

Subject	Stride Length (m)						Stride Duration (s)					
	Normal Walking			Strap Walking			Normal Walking			Strap Walking		
	Len	StD	CV	Len	StD	CV	Dur	StD	CV	Dur	StD	CV
1	1.27	0.19	0.15	1.30	0.17	0.13	1.11	0.06	0.06	1.13	0.08	0.07
2	1.34	0.19	0.15	1.31	0.23	0.17	1.01	0.06	0.06	1.02	0.06	0.06
3	1.16	0.21	0.18	1.19	0.13	0.11	1.10	0.06	0.05	1.08	0.04	0.04
4	1.11	0.25	0.22	1.19	0.19	0.16	1.07	0.11	0.10	1.07	0.09	0.09
5	1.30	0.16	0.13	1.31	0.18	0.14	1.07	0.08	0.07	1.08	0.06	0.05
6	1.43	0.13	0.09	1.37	0.18	0.13	0.99	0.04	0.05	0.99	0.03	0.03
7	1.35	0.22	0.16	1.37	0.16	0.12	1.00	0.07	0.07	1.04	0.07	0.07

Len = Length (m), StD = Standard Deviation, CV = Coefficient of variance, Dur = Duration (s).

6.3.3 FIMP End-Swing Tripping Effectiveness

Perturbations during the end-swing gait phase induce the lowering recovery strategy [49], which correspond to the lowering of the perturbed leg before raising the contralateral leg to overcome the obstacle (Figure 6.23). This section studies the effect of the trip on the ipsilateral leg (perturbed left leg) and the contralateral leg (right leg). ANOVA with SPM is employed to identify the time instance when the perturbed gait cycle deviates from NormalWalking and StrapWalking. The raw data motion capture data is also filtered with 2^{nd} order Butterworth low pass filter at $6Hz$ before the joint angles are extracted.

Figure 6.23: End-swing fall sequence induced by the brake attached to the subject's ankle via a wire.

Left Leg

The gait cycles of the left leg, which contains the instance of perturbation, is averaged for all subjects' EndSwing trip trials (ES) and shown in Figure 6.24. Results showed that the ipsilateral hip joint did not exhibit any significant differences from NormalWalking (NW) and StrapWalking (SW). However, the knee joint experienced

less extension, while the ankle joint underwent higher plantarflexion at the end of the swing phase.

The lack of difference at the hip joint implies that the perturbation happened precisely at the end-swing phase. During a normal swing phase, the hip flexion muscles contract to swing the thigh, shank and foot forward. The thigh antagonist muscle relaxes to allow the momentum of forward walking and swinging thigh to swing the shank forward passively. Since the tripping mechanism arrested the ankle at the end-swing phase, the hip has mostly expended its rotational kinetic energy and is mostly staying static in space with the help of the thigh muscles. Therefore, only the passively swinging shank and the attached foot kinematics were significantly disturbed.

The effect of the tripping mechanism was most evident in the knee joint during the end-swing phase. When the tripping mechanism arrests the ankle, the shank is no longer able to swing forward, causing the knee flexion angle to stay high even after the current gait cycle has ended. In spite of that, the knees can still perform some slight extension motion due to the body leaning forward. The forward leaning of the whole body also brings the shank and foot closer to the ground, preventing the knees from further extending. Consequently, the foot has higher plantarflexion at end-swing to increase the air-time of the body for widening of the contralateral limb. This higher plantarflexion is also observed in other trip studies [204, 205].

The posthoc analysis of the combined subjects' data using 2 sample t-test and Bonferroni-corrected p-value is shown in Figure 6.25. The results showed that the left leg during EndSwing trials exhibited similar significant differences to both the NormalWalking and StrapWalking trials.

Right Leg

The right leg gait cycles that happened immediately after the left leg's perturbation were extracted and averaged for all subjects' EndSwing trials (ES) (Figure 6.26). The stance phase of the right leg happened concurrently as the swing phase of the left leg, which contained the perturbation. When the perturbation occurred, the contralateral right leg has to quickly raise the thigh while the ipsilateral left leg extends its knee to cushion the trip impact, and plantarflex its ankle to increase air-time. This rise in hip flexion angle is observed in the second row SPM chart for the hip. Significant differences were found even before the swing phase has started (swing phase starts at 60% stride, demarcated by the vertical dotted line). Subsequently,

EndSwing Left Leg ANOVA

Figure 6.24: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs EndSwing (ES) trials for the left leg with SPM. The left leg is attached to the ankle straps with a brake at the opposite end. Top row indicates the mean hip, knee and ankle flexion angles for all subjects and standard deviation clouds; mean ($\pm$ st.dev). Second row indicates the ANOVA test on the data shown in top row. Third row shows a colour map highlighting significant differences of the ANOVA result in second row. The last row shows the significant different effect size of individuals. Significant differences are observed in the knee and ankle joints near the end-swing phase.

All Subject EndSwing Left Leg Post Hoc

Figure 6.25: Posthoc analysis of the Endswing trip trials for the left leg.

the hip joint continued in its trajectory to flex and brought the thigh and shank forward extending the body's BoS. The knee experiences higher than normal flexion as observed in the significant difference seen in the end-swing phase. This higher knee flexion is caused by shorter than normal swing phase, not allowing sufficient duration for proper knee extension. The higher knee flexion also has the advantage of absorbing more of the touchdown impact. Additionally, the ankle has more pronounced plantarflexion at the initial swing phase in preparation for an earlier than usual heel strike, and also to act as a spring to absorb the higher touchdown impact.

Subject 7 walked with a pronounced upright fashion (like a ballroom dancer), leading to a walking posture with an elevated forward leaning angle as compared to other subjects. Therefore, it is hypothesized that the end-swing trips affected his thigh much more severely because he needs to raise his thigh faster to compensate for the faster falling momentum. Observations in subject 7 with other subjects are not observed in the mid-swing trip because all of them are in their most upright pose during the mid-swing phase.

The posthoc analysis of the combined subjects' data using 2 sample t-test and Bonferroni-corrected p-value are shown in Figure 6.27. The results showed that, like the left leg, the right leg during EndSwing trials exhibited similar significant differences to both the NormalWalking and StrapWalking trials.

EndSwing Right Leg ANOVA

Figure 6.26: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs EndSwing (ES) trials for the right leg with SPM. The right leg is attached not attached to any ankle straps. Top row indicates the mean hip, knee and ankle flexion angles for all subjects and standard deviation clouds; mean ($\pm$ st.dev). Second row indicates the ANOVA test on the data shown in top row. Third row shows a colour map highlighting significant differences of the ANOVA result in second row. The last row shows the significant different effect size of individuals. The hip joints have the most pronounced differences when comparing to NW and SW. The knee joint has experiences lower extension angle at the end-swing phase, while the ankle joint has lower plantarflexion at the early swing phase.

All Subject EndSwing Right Leg Post Hoc

Figure 6.27: Posthoc analysis of the Endswing trip trials for the right leg.

Discussion

This end-swing trip results implied that the end-swing tripping system can replicate the lowering strategy as mentioned by other research [49, 57]. The induced trip kinematics and recovery strategies are also repeatable and can be replicated among multiple subjects.

The individual subject's end-swing FIMP analysis for their left and right leg is shown in Appendix L

6.3.4 FIMP Mid-Swing Tripping Effectiveness

Perturbations during the mid-swing gait phase induce the elevating recovery strategy [49], which correspond to an immediate raise of the perturbed leg to overcome the obstacle (Figure 6.28). However, in this experiment, the brake's activation timing was lengthened to arrest the leg's kinematics for most of the swing phase. This mimics situations where the swing leg gets tangled on some rope or is in contact with some tall obstacles that the elevated toe clearance cannot overcome.

Similar to Section 6.3.3, ANOVA is used for statistical analysis, and the motion-captured data are filtered at $6Hz$ before extracting the joint angles.

Figure 6.28: Mid-swing fall sequence induced by the brake attached to the subject's ankle via a wire.

Left Leg

The gait cycles of the left leg with perturbations are averaged for all subjects' MidSwing trip trials (MS) and shown in Figure 6.29. The results indicated that there are significant differences in all 3 joints during the swing phase. Due to the tripping mechanism activating at early to mid-swing phase, the hip has lower flexion throughout the majority of the swing phase. On the contrary, the knee joint experienced higher flexion angles during the mid to late swing phase. The ankle has significantly higher plantarflexion for the majority of the swing phase. The appearance of significant differences throughout the swing phase indicated that the tripping mechanism had successfully tripped the subject at the early to mid-swing phase.

The lower hip flexion angle was caused by the tripping mechanism stopping the left leg from moving forward. This behaviour is not observed in the end-swing trip because the hip joint is already at the maximum flexion pose at the instance of trip. The hip flexion continues forward slightly after the instance of perturbation because of the excessive forward momentum, the forward leaning of the upper body and the deactivation of the tripping brake after 250 ms.

The knee joint experiences a similar low knee extension scenario as end-swing trip, but to a greater degree. This happened because the ankle was arrested much earlier than end-swing, preventing majority of the knee extension from occurring.

As the brake continues to hold onto the ankle after the subject has felt the mid-swing trip, the subject tries to reach for the ground with ankle plantarflexion, observed by the significant ankle plantarflexion throughout the whole swing phase.

The posthoc analysis of the combined subjects' data using 2 sample t-test and Bonferroni-corrected p-value is shown in Figure 6.30. The results showed that the left leg during MidSwing trials exhibited similar significant differences to both the NormalWalking and StrapWalking trials.

It is hypothesised that the hip flexion angle will increase instead of decreasing (as compared to NormalWalking and StrapWalking) if the brake activation timing was

MidSwing Left Leg ANOVA

Figure 6.29: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs MidSwing (MS) trials for the left leg with SPM. The left leg is attached to the ankle straps with a brake at the opposite end. Top row indicates the mean hip, knee and ankle flexion angles for all subjects and standard deviation clouds; mean ($\pm$ st.dev). Second row indicates the ANOVA test on the data shown in top row. Third row shows a colour map highlighting significant differences of the ANOVA result in second row. The last row shows the significant different effect size of individuals. Significant differences are observed in the knee and ankle joints near the end-swing phase.

All Subject MidSwing Left Leg Post Hoc

Figure 6.30: Posthoc analysis of the Midswing trip trials for the left leg.

shortened. This is because the true elevating strategy of the leg can be observed. The perturbed leg can rise above and step over the obstacle. However, the knee should remain in this elevated flexed position due to the forward leaning of the body, shortening the time till heel strike.

Right Leg

The gait cycles of the right leg immediately after the MidSwing (MS) perturbation on the left leg is averaged on all subjects and shown in Figure 6.31. The most obvious observation is the significant difference in hip flexion angle that happened as early as the early swing phase. The knee joint experienced lower flexion during the swing phase and the ankle had a relatively constant joint angle throughout the entire gait cycle.

The hip joint showed a significant difference in the early stance phase because the early-mid-swing perturbation on the left leg corresponded to the beginning of the stance phase on the right leg. As the perturbation occurred, the whole body leaned forward, exerting its entire body weight on the right leg alone. This caused excessive hip joint flexion during the stance phase.

Since the left leg remains immobilized by the brake, all subjects reduced the

induced unwanted angular momentum by skipping the right leg forward. This widened the BoS and allowed stability to be regained. The skipping action allows the hip to flex and bring the right foot forward, widening the BoS and allows stability to be regained. No hip extension was observed as the end of swing phase which signified the end of the skipping phase.

Reduced knee flexion was observed in the swing phase because during skipping interval, the body was trying to widen the BoS along with the increased hip flexion. There was no difference in the knee flexion angle during stance phase because the whole body pivoted on the ankle and skipped forward rather than bending the knees to absorb the unwanted momentum.

The ankle joint acted as the pivot for the whole body to lean forward during the stance phase. Additionally, the ankle joint is responsible for generating the push off force to allow for skipping action to occur. This was observed by the reduced ankle flexion during the end stance phase. The ankle maintained its neutral pose after toe-off during the skipping motion to brace for impact.

The posthoc analysis of the combined subjects' data using 2 sample t-test and Bonferroni-corrected p-value is shown in Figure 6.32. The results showed that, like the left leg, the right leg during MidSwing trials exhibited similar significant differences to both the NormalWalking and StrapWalking trials.

Discussion

The induced mid-swing trip of the current experiment managed to immobilize the left ankle at the early to mid-swing phase. However, the recovery strategies employed does not follow the elevating strategy that is widely accepted to be indicative of mid-swing trip [51]. Instead, subjects skipped forward on their contralateral right leg to increase their BoS and reduce unwanted dynamics. This difference is likely attributed to the duration of the brake activation duration. This phenomenon has previously been reported but they are using a different fall inducing method [52]. Since the current experiment arrested the ankle for 250 ms, the duration for fall recovery has already been expended by more than half. The subjects' body sensed this and chose to adopt the skipping strategy to regain stability.

Despite the non-replicative elevating strategy, these results still showed that mid-swing trip kinematics can be repeated, even among multiple subjects.

The individual subject's mid-swing FIMP analysis for their left and right leg is shown in Appendix M

MidSwing Right Leg ANOVA

Figure 6.31: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs MidSwing (MS) trials for the right leg with SPM. The right leg is not attached to any ankle straps. Top row indicates the mean hip, knee and ankle flexion angles for all subjects and standard deviation clouds; mean ($\pm$ st.dev). Second row indicates the ANOVA test on the data shown in top row. Third row shows a colour map highlighting significant differences of the ANOVA result in second row. The last row shows the significant different effect size of individuals. Significant differences are observed in the knee and ankle joints near the end-swing phase.

All Subject MidSwing Right Leg Post Hoc

Figure 6.32: Posthoc analysis of the Midswing trip trials for the left leg.

6.4 Conclusion

This chapter proposes an automatic fall inducing movable platform (FIMP) to tackle the problem of treadmill-based and non-repeatability fall inducing systems. The proposed solution (FIMP) uses a simple follow-me technology to move the whole platform with the subject, and gait phase identification to properly synchronise and induce fall reliably (Operating flowchart is shown in Figure 6.19).

The gait phase detection algorithm has been created using a bandpass filter and Levenberg Marquardt algorithm. It reliably generate an analogue phase angle for different gait patterns such as walking speed, gait initiation/termination and changing heading angle.

Follow-me functionality was achieved with Intel RealSense depth camera. A simple average of all the point cloud allows for the estimation of body centre. This body centre was used to calculate the distance of the body to the platform and also the body's heading angle.

The trip and slip functionality of FIMP was achieved by using a brake and motor respectively. Its fall severity can be adjusted by tuning the ON timing of the brake and motor or asking the subject to alter their walking speed. A faster walking speed correlates to a higher severity fall. The brake has a holding force of 348N while the

motor has a pulling force of 110N.

Experimental results showed that FIMP can retain its transparency to the users except for a slight increase in ankle flexion during the mid-swing phase. This was due to the usage of an ankle strap which hindered the ankle freedom of performing plantar/dorsiflexion. Trips results showed that FIMP induced trips at the correct gait phase timing with good repeatability. End-swing trips replicated the lowering strategy that was described by other research [49, 57]. On the other hand, subjects adopted the lesser-known skipping strategy [52] to recovery from the mid-swing trips. This is likely attributed to the current mid-swing trip setup mimicking a rope entangling the ankle rather than a short obstacle contacting the ankle during mid-swing phase.

Nonetheless, integration of the gait phase detection system, follow me functionality and fall inducing mechanisms into FIMP allowed investigators to induce falls at a specific gait phase. Hence, falls can be generated reliably and repeatedly.

The results of using FIMP to validate the exosuit performance is further discussed in Chapter 7.

6.5 Future Work

The transparency of FIMP can be further improved to reduce the slight ankle flexion observed on some subjects. This can be achieved by controlling the ankle strap tightness and reducing the tension force used to keep the wire taut.

The study of trips should also be repeated with shorter brake activation timing during the mid-swing phase. The goal is to determine the threshold that can reliably allow researchers to induce either the elevating or the skipping strategy.

A more detailed study can be done by collecting the trip induced dynamics. The study of force will allow assistive forces to be estimated. Subsequent steps following the perturbation should also be followed up, as they are still responsible for eliminating certain fall momentum.

Chapter 7

System Performance

Chapters 3 to 5 described all the components and their validation results necessary to create an exosuit. The exosuit aims to detect fall and provide assistive forces during near fall scenarios. In addition, Chapter 6 described a Fall Inducing Movable Platform (FIMP) that can reliably induce a trip without impeding the normal gait movements. FIMP facilitates the collection of fall data to validate the capabilities of the integrated exosuit.

In this chapter, all the components are integrated as a completed exosuit. An evaluation will be performed on the exosuit by using FIMP to induce realistic trips. The method of data collection is first reported, followed by data processing, linear velocity estimation from IMU, and finally, the efficiency of the exosuit in assisting balance recovery based on several balance indicators.

7.1 Experimental Setup

All kinematic data were collected according to protocols approved by SZU IRB (20190012).

A total of 8 male and 7 female subjects were recruited for the experiment. They have an average age of 22.75 ± 0.90 years, average height of 164.13 ± 7.98 cm, average weight of 57.45 ± 10.01 kg, and an average BMI of 21.17 ± 2.28 . All of them has no history of locomotor impairment, neurological impairment or cardiovascular diseases. All subjects passed the Modified Clinical Test of Sensory Interaction in Balance (CTSIB-M) with full scores and do not have any history of balance deficiency. CTSIB-M has been proven to be one of the few balance measures that can predict falls [206, 207].

The experiment is separated into three stages. The first stage collected representative ADLs, and the second stage collected the induced lumbar extension angle

upon actuator activation from a static posture. Finally, the third stage collected subjects kinematics with and without exosuit assistance during near-fall scenarios.

All kinematics data were collected with 3-Space™ USB/RS232 IMUs obtained from *Yost Labs* (see Appendix G.1). All subjects have 5 IMUs strapped onto their shank, thigh and torso, identical to the experimental setup in Section 3.3.2.

1st Stage: Collection of ADLs

Several motion were added to the experiment mentioned in Section 3.3.2. These actions encompass more variability of ADLs in posture, speed and direction. Specifically, they included walking at different speeds and reaching from the front and sides at different heights. A total of eighteen motion were recorded for our study. These 18 motion were:

1. Standing still
2. Walking at normal speed along an L-shaped pathway (Figure 7.1a)
3. Walking at slow speed along an L-shaped pathway (Figure 7.1a)
4. Walking at fast speed along an L-shaped pathway (Figure 7.1a)
5. Walking sideways (left and right) (Figure 7.1b)
6. Walking backwards (Figure 7.1c)
7. Bending forward and pick up an object on the floor at half-arm length with locked knees (Figure 7.1d)
8. Bending forward and pick up an object on the floor at half-arm length with slightly bent knees (Figure 7.1e)
9. Bending forward and pick up an object on the floor at half-arm length with fully bent knees (Figure 7.1f)
10. Reaching forward for an object at waist height, placed at one-arm length (Figure 7.1i)
11. Reaching forward for an object at shoulder height, placed at one-arm length (Figure 7.1h)

12. Reaching forward for an object at head level, placed at one-arm length (Figure 7.1g)
13. Reaching forward for an object at waist height, placed anteriorly at a distance half of the subject's height (Figure 7.1i)
14. Reaching forward for an object at shoulder height placed medially at a distance half of the subject's height (Figure 7.1h)
15. Reaching forward for an object at head level placed medially at a distance half of the subject's height (Figure 7.1g)
16. Reaching sideways for an object at waist height, placed medially at a distance half of the subject's height
17. Reaching sideways for an object at shoulder height, placed medially at a distance half of the subject's height
18. Reaching sideways for an object at head level, placed medially at a distance half of the subject's height

Subjects walking along the L-shaped pathway were instructed to turn with the sequence of left 90 deg, right 180 deg, right 90 deg and left 180 deg (Figure 7.1a). This allows different turning directions and angles to be captured. When subjects were instructed to bend forward with their knees locked, they were informed that it was not critical for them to reach the object on the floor. All motion were repeated thrice in each trial, except for the walking motion. A total of three trials were collected per subject, and each trial consisted of a run of all 18 motion.

2nd Stage: Collection of Actuator induced Lumbar Flexion

Although exosuit stiffness can be estimated based on physical parameters (Chapter 4), the actual induced lumbar flexion, given an actuator output, has not been evaluated. Hence, the second stage measures the lumbar flexion at different levels of actuator output force. These results will help determine the individualised actuator force settings in the future.

To measure effective lumbar flexion angle, subjects were requested to wear the base-suit with its attached actuator (Figure 4.1). Details on base-suit and actuator integration was given in Section 5.5 and shown in Figure 5.12. The actuator (Figure 5.8) was secured to an extended aluminium profile of FIMP (Figure 5.11). The output

Figure 7.1: Experimental protocols used to replicate activities of daily living. These motion include (a) walking along a pathway, (b) side-walking, (c) backwards-walking, (d) Bend forward with knees locked, (e) bend forward with bent knees, (f) full squat, (g) reaching at head height, (h) reaching at shoulder height and (i) reaching at wasit height

from the actuator is a 6mm diameter rope which was attached to a wire rope that ran through a series of bearings. Then, the wire rope from the bearings passed through a Bowden cable sheath before terminating at the T5 region of the subject (Figure 7.2).

Figure 7.2: The actuator attached to the back of the subject. The output from the actuator runs through a series of bearings that goes into a Bowden cable input. The Bowden sheath terminates at the base of the seat harness, and the wire rope extends from the sheath to the T5 region of the human spine.

The actuator was set to 3 different force levels: $7kg$, $19kg$ and $26kg$. For each force level, the subjects adopted an initial position by flexing their torso at an angle of 15 deg, 30 deg, 45 deg. Subjects were wearing an IMU across their chest, which outputs their lumbar flexion angle onto a computer screen for them to adjust and maintain their position.

At each flexion angle, the actuator was activated and applied a contracting force

between the subject's waist and torso. All subjects were instructed not to resist nor assist the actuator force, but rather, allow the actuator to induce torso extension. The stabilised lumbar flexion angle after the force application was recorded as the resultant angle. Every combination of actuator force setting and lumbar flexion angle was repeated three times for each subject (Table 7.1). The lumbar flexion trials per subject was 27 times.

An upper limit of 45 deg was chosen for this experiment as empirical data has shown that lumbar flexion of $38.7 \text{ deg} \pm 10.9 \text{ deg}$ and 45.2 deg at recovery foot contact is most likely to belong to fallers executing lowering and elevating strategies respectively [208]. Lumbar flexion showed high correlations with falling during both types of trip recovery strategy [208].

Table 7.1: Actuator induced Torso Flexion Tests

Actuator Force (kg)	Flexion Angle (deg)	No. of Trials
7	15	3
19	15	3
26	15	3
7	30	3
19	30	3
26	30	3
7	45	3
19	45	3
26	45	3

Although the collected lumbar flexion angles were induced from a static position, it remains useful for dynamical situations. As the torso momentum increases during a trip, the actuator force required to arrest the torso dynamics also increases. However, it is difficult to control all variables during dynamical situations such as BoS, muscle activation and lean angle. Hence, static tests offer an insight into the force magnitude required at different situations through comparison of the estimated dynamical force with the gravitational force on the torso at different flexion angles.

3rd Stage: Collection of fall data

FIMP was used to induce trips upon the subjects as described in Section 6.2.2. This stage of the experiment was divided into two segments: 1) Fall recovery without exosuit assistance (noExo) and 2) Fall recovery with exosuit assistance (Exo-assist).

For both segments, subjects began by walking at their normal speed along a straight pathway, with FIMP automatically following behind (Figure 7.3). Upon the trigger of the "Fall" button, the micro-controller will initiate the gait phase identification process. When the desired gait phase was detected, the brake was activated and arrested the ankle movement. Only lowering strategy and skipping strategy trips were induced in this experiment. Skipping strategy was defined in Section 6.3.4.

The Exo-assist trials require the exosuit to activate its actuator to provide assistive torso extension forces, while the noExo trials do not. The activation of the actuator depends on the fall detection algorithm detecting the fall through data collected from the IMUs. The fall detection algorithm performs independently from the gait phase detection algorithm, and no data is shared between them. When the fall detection algorithm detects a sufficiently severe fall, it triggers the actuator. The severity of a detected fall can be tuned by changing the threshold of the probability output from the fall detection algorithm. However, reducing the threshold may lead to higher chances of false alarm (Section 3).

During the actuator activation, its first stage that was designed to eliminate most of the system elasticity will trigger for $100ms$. After which, the second stage will automatically activate to apply the remaining assistive force.

Figure 7.3: Experimental flow for the testing of the exosuit for fall recovery assistance. In (a), the subject starts with a normal gait. The gait identification system (b) identifies the correct gait for inducing a trip or a slip and sends the signal to FIMP. FIMP induces the fall in (c). As the subject falls, the fall detection system detects the fall (d) and sends a signal to the exosuit actuators. The actuators activate (e), leading to assisted fall recovery (f).

Subjects began with attaching a safety rope from the top horizontal bar of FIMP to their torso harness. The torso harness doubled as the anchor point for the actuator's Bowden cable. The differences between noExo and Exo-assist trials were the usage of seat harness and the attachment of the actuator's Bowden cable for the Exo-assist trials. For both segments of this experiment, a minimum of six trips was randomly induced as subjects walk along a straight pathway. Three of the falls were induced in the early to mid-swing phase (mid-swing) and another three in the mid to end-swing phase (end-swing) to encourage the execution of the elevating and

skipping fall recovery strategy respectively. As a result, each subject underwent a minimum of 12 trips for the entirety of the 3rd stage experiment (Table 7.2). The same FIMP settings were used for both noExo and Exo-assist trials.

Table 7.2: noExo and Exo-assist Tests

Test	Gait Phase	number of falls
noExo	Mid-swing	3
noExo	End-swing	3
Exo-assist	Mid-swing	3
Exo-assist	End-swing	3

This collected fall data from 15 subjects are evaluated together with another 3 subjects in Chapter 3 for pre-impact fall detection accuracy.

7.2 Results and Discussion

All analysis in the following sections was made between noExo and Exo-assist for three different categories, namely mid-swing, end-swing and combined total falls. Mid and end-swing trips induce different recovery actions affects the balance indicators differently. However, certain individuals may perform similar recovery strategies, even with different kinds of trips. Hence, the combined results from mid and end-swing are also compared.

7.2.1 Actuator Induced Torso Flexion

The actuator induced lumbar flexion at 7, 19 and 26kg is reported in Table 7.3. Vertical torso position was initialised as 0 deg, and bending forward increased the magnitude of the flexion angle. The actuator can induce significant torso extension at all tested flexion angles using the 26kg CFS. Therefore, experiments in the 3rd stage of exosuit evaluation will use the 26kg CFS.

Induced extension increases (decreasing magnitude) as CFS force increases. On the contrary, decreasing initial lumbar flexion results in lower induced extension (Figure 7.4). Reduction in induced flexion can be attributed to the lower compression elasticity of the spine as the flexion angle increases. During an ideal upright position, the lumbar and cervical spines form an inward curve (lordotic), while the thoracic and sacral spine forms an outward curve (kyphotic) (Figure 7.5). The anchor points of the actuator are situated between the S1 and T5 spine which surrounds the

lumbar spine, forming an inward curve. If the actuator activates at the standing position, it compresses the inward curve, creating a curve with a smaller radius of curvature, leading to torso extension. However, as the torso flexes from 0 deg to 45 deg (Figure 7.6), the inward curve increases in its radius of curvature, creating a spine with greater rigidity. This is because spine bending requires less energy than spine compression. Therefore, when actuator activates at high flexion, most of the force is absorbed by the vertebrae and intervertebral disks in the longitudinal direction. This conclusion also implies that it will be advantageous to detect near-falls as soon as possible to increase the actuator effectiveness in inducing torso extension.

Table 7.3: Actuator induced Torso Flexion Results

Actuator Force (kg)	Init Flexion Angle (deg)	Average Flexion (deg)	Standard Deviation (StD)	Δ Flexion (deg)
7	15	14.25	0.48	-0.75
19	15	10.38	1.89	-4.63
26	15	8.81	1.77	-6.19
7	30	29.75	0.38	-0.25
19	30	26.10	1.60	-3.90
26	30	25.96	1.75	-4.04
7	45	44.82	0.37	-0.18
19	45	42.33	1.59	-2.67
26	45	41.82	1.52	-3.18

7.2.2 Exosuit Capabilities

The capabilities of the exosuit in assisting fall recovery can be evaluated by looking at different balance indicators. An improvement in the balance indicator results will indicate that the exosuit can assist in fall recovery. Section 2.4 included the definition of different well-known balance indicators. However, these indicators have their limitations:

Center of Mass (CoM): Does not include the effects of dynamical forces.

Center of Pressure (CoP): Include dynamical forces, but its limited region of balance calculation prevents it from being useful in normal circumstances. Normal walking has already been proven to have CoP that exceeds the boundaries of the sole.

Figure 7.4: Induced torso extension angle vs different magnitude of CFS at different initial flexion angle. All induced forces are at 7, 19 and 26 kgf, but the 30 deg and 45 deg curves are shifted right by 0.5kgf and 1.0kgf intentionally to allow for easy identification of the standard deviation bars.

Zero Moment Point (ZMP): Similar to CoP, if ZMP lies within the area under the sole. However, they face the limitation of not including momentum (velocity) of the body masses. A moving human can still fall even if there are no external forces on their body except for gravity.

AngMom: Regulation of the AngMom is vital to achieving gait stability, usually by swinging the limbs in the opposite direction during gait [171]. When a fall occurs, excessive AngMom gets injected into the system [51], and the body must synchronise its movement to reduce the AngMom to normal levels.

Extrapolated Center of Mass (XCoM) /Capture Point: Uses the instantaneous velocity of the CoM to calculate the point at which to step in order to reduce CoM's velocity to zero. However, it assumes that the legs can take the load of the momentum.

For this project, it is required to consider the effects of dynamical forces on the body. Hence, CoM is removed as a viable balance indicator. CoP is also not considered as it is assumed that it will not function for fall scenarios, given that it does not work well even during normal walking. AngMom has been proven in Chapter 3 that it is not feasible to function as an accurate fall detection. Hence, it is also excluded from the balance indicators. The remaining balance indicators (XCoM, ZMP) will

Figure 7.5: Structure of a normal human spine. Ideally, the lumbar and cervical spines are lordosis curves (inward) and thoracic and sacral spines are kyphotic curves (outward). The Bowden cable of the actuator is attached between T5 and S1 spine. Image obtained from [209]

each be compared between noExo and Exo-assist trials to determine if the exosuit has provided any balance recovery assistance.

Velocity Dependency of balance indicators

The severity of falls depends significantly on the gait velocity of the subject at the instance of a trip; the magnitude of the balance indicators will also be significantly affected by the gait velocity. Conventionally, to remove the dependency of a variable from an indicator, a division of the indicator by a factor of the variable will be sufficient. However, the velocity of the subjects varied greatly, coupled with the fact that several trials have velocities that were very close to zero, making the usage of division to remove dependency unsuitable.

A simple solution is proposed. If there are no significant differences between the velocity values from noExo and Exo-assist trials, it will be possible to compare their results as it is. Pelvis forward linear velocity is used to represent the gait speed of the subject (Section 3.4.3). An SPM analysis is used to compare the gait speed of all subjects' 600 samples (about 2.5 seconds) before the trip initiation. The 2 sample t-test is used with a 0.05 p-value.

Figures 7.7 and 7.8 show the SPM analysis of the subjects' pelvis velocity, 600 samples before undergoing end-swing and mid-swing trips. It can be seen that there

Figure 7.6: Lumbar flexion (left to right) leads to a larger radius of curvature for the lumbar inward curve (green line). This directs the actuator force (yellow) to change from the initial spinal torsional force to tensile force. Torsion force creates torso extension as the lumbar spine forms a smaller inwards curve. Since the spine is easier to bend than compress, the actuator effectiveness in inducing torso extension decreases as lumbar flexion increases.

is no significant differences between noExo and Exo-assist pelvis velocity values at all time instances. Hence, it is possible to compare the balance indicators in the subsequent sections as they are, without removing their velocity dependencies.

Zero Moment Point

The maximum magnitude of ZMP of every trip trials (normalised by subject's height) is compared between noExo and Exo-assist in Table 7.4. ZMP calculation is shown in Section 2.4.2. The acceleration and positional data used in the calculation of the ZMP has been filtered with a 2^{nd} order Butterworth filter at $25Hz$ and $6Hz$ respectively.

Since the vertical axis of ZMP is always set to zero, magnitude of ZMP is calculated via:

$$ZMP = \sqrt{x_{zmp}^2 + z_{zmp}^2} \quad (7.1)$$

where ZMP_x and ZMP_z is the x and z component of the ZMP.

Mann Whitney one-tailed test was conducted for ZMP between noExo and Exo-assist trials for mid-swing, end-swing and their combined results (Table 7.4). None of the trip conditions exhibited any significance between noExo and Exo-assist trials. This indicated that the exosuit did not significantly reduce acceleration in both the global posterior and medial/lateral direction.

Figure 7.7: SPM analysis of pelvis velocity from all subjects during End-swing. Each of the 3 dimensional axis is compared and no significant differences are found.

Table 7.4: Maximum ZMP

Trip Phase	noExo		Exo-assist		p-value
	ZMP mean [m]	ZMP StD	ZMP mean [m]	ZMP StD	
Mid-Swing	2.131	3.942	3.335	5.089	4.360e-01
End-Swing	0.658	0.867	1.114	2.100	6.513e-02
Combined	1.365	2.897	2.214	4.035	1.328e-01

Sagittal Plane ZMP: Since the actuator is only assisting in sagittal plane torso extension, one might argue that the roots of squares of the ZMP may not be a good

Figure 7.8: SPM analysis of pelvis velocity from all subjects during Mid-swing. Each of the 3 dimensional axis is compared and no significant differences are found.

actuator performance indicator. Hence, Table 7.5 shows the ZMP (normalized by leg length) in only the Z-axis (anterior-posterior). A positive ZMP value indicates the ZMP is posterior of subject's CoM.

Similar to the x and z-axis normalised ZMP, no significance was found between all trip trials for noExo and Exo-assist conditions. Hence, the same conclusion that the exosuit did not assist significantly in posterior acceleration can be formed.

Extrapolated Center of Mass

XCoM or Capture Point (normalised by subject's height) is compared between noExo and Exo-assist in Table 7.6. XCoM calculation is shown in Section 2.4.4. Similar

Table 7.5: Maximum Sagittal ZMP

	noExo		Exo-assist		
Trip Phase	ZMP mean [m]	ZMP StD	ZMP mean [m]	ZMP StD	p-value
Mid-Swing	-9.782	58.169	-1.933	4.203	3.619e-01
End-Swing	-0.588	1.391	-1.004	2.598	4.230e-01
Combined	-4.962	40.395	-1.465	3.517	4.805e-01

to the ZMP calculation, the maximum XCoM value is only calculated when the anterior-posterior axis (z-axis) XCoM value is anterior of the subject's CoM.

The vertical axis of XCoM is always set to 0, hence the magnitude of XCoM is calculated as:

$$XCoM = \sqrt{x_{com}^2 + z_{com}^2} \quad (7.2)$$

Mann Whitney one-tailed test was conducted for XCoM between noExo and Exo-assist trials for mid-swing, end-swing and their combined results (Table 7.6).

All the trials between noExo and Exo-assist conditions showed high significance ($p < 0.01$). This result implied that the exosuit can significantly reduce the velocity of the user during a trip. Reducing unwanted velocity is more important than reducing acceleration in a trip scenario because acceleration induced from the perturbation is only applied at an instance, while the induced velocity is accumulated over time with a sudden increase during perturbation.

Table 7.6: Maximum XCoM

	noExo		Exo-assist		
Trip Phase	XCoM mean [m]	XCoM StD	XCoM mean [m]	XCoM StD	p-value
Mid-Swing	0.244	0.041	0.217	0.033	6.995e-04
End-Swing	0.228	0.021	0.199	0.025	5.912e-03
Combined	0.239	0.037	0.208	0.031	2.609e-05

Sagittal XCoM: Similar to the sagittal plane argument in ZMP, the sagittal XCoM (normalized by leg length) is presented in Table 7.7.

The significance of XCoM reduction decreases when comparing only in the sagittal plane. When comparing just the mid-swing and end-swing phases sepa-

Table 7.7: Maximum Sagittal XCoM

	noExo		Exo-assist		
Trip Phase	XCoM mean [m]	XCoM StD	XCoM mean [m]	XCoM StD	p-value
Mid-Swing	-0.181	0.129	-0.137	0.087	6.733e-02
End-Swing	-0.216	0.123	-0.182	0.103	7.011e-02
Combined	-0.199	0.127	-0.158	0.097	1.150e-02

rately, the reduced XCoM did not show sufficient significance. However, when the trips of different phases were combined, the effect of the exosuit became significant again. This result differed from the normalised XCoM comparison because of the high variability between subjects in the sagittal plane. Adding more subjects or trials will most likely meet the requirement for significance, similar to the XCoM comparison.

Discussion

Among the 2 balance indicators used to evaluate the exosuit performance, XCoM managed to show that the exosuit can significantly improve the stability of the user during trips. On the contrary, ZMP did not detect any significance between noExo and Exo-assist.

XCoM is identified as the more reliable balance indicator for evaluating the exosuit because of its inclusion of velocity during calculation. It is known that a static individual with forward velocity but zero acceleration can still fall because there are no opposing forces to eliminate that velocity. However, an individual with zero velocity will be stable. Additionally, the induced acceleration from a perturbation will only appear for a short time instance, while the individual will accumulate the generated velocity. Hence, XCoM, which accounts for velocity, is more suitable to judge the instantaneous stability of a subject as compared to ZMP, which accounts only for acceleration vectors. XCoM is also the preferred evaluation tool for stability among other fall intervention solutions [13, 14].

Significant effects were seen only with XCoM but not ZMP which also implies that the actuator of the exosuit is not successful in transmitting its $26kg$ of force to the subjects' torso. If the transmission efficiency is 100%, a sharp deceleration will occur, and it will show up in the ZMP indicator. However, the lack of significance between noExo and Exo-assist suggests that the forces felt by the subject are not

significant to produce an observable ZMP outcome. On the contrary, significance with XCoM shows that the actuator can reduce the anterior velocity of the subject. This indicates that majority of the actuator force has been lost and locked in the transmission mechanism. Hence, the locked actuator can prevent the subject from further lumbar flexion, but it cannot assist in active torso extension. This is inline with subject's feedback that they cannot feel significant torso extension force from the actuator, other than the tightening of the base-suit and that their lack of ability to perform lumbar flexion. When subjects voluntarily extend their lumbar, the locked actuator is briefly unlocked because of the reduced tension. This allows the actuator to reel in any cable slack before locking itself again. Therefore, the actuator acts like a clutch that only allows torso extension when activated.

Since XCoM indicates that the exosuit can assist in recovering the stability of its user during a trip, the hypothesis stated in Chapter 1 is proven here. The hypothesis states that *the proposed novel soft exosuit can serve as a fall intervention device that assists in restoring stability after a fall onset.*

7.2.3 Exosuit Limitations

Several limitations exist with the exosuit and its surrounding experiments. They are discussed in the following order:

1. Experimental Design
2. Evaluation Process
3. Exosuit Design

Experimental Design

The most obvious limitations when considering any fall experiments is whether the knowledge of fall will alter the subject's gait pattern. Anticipatory responses of the trip have previously been shown to increase step length, increase toe height, and increase mediolateral trunk acceleration and velocity [147, 210, 211]. Mixed changes in step width are reported [147, 211]. Nevertheless, observable changes do occur in the calculated gait parameters and kinematics when subjects are anticipating for a fall. The effect of these anticipatory responses will increase the subject's stability at the expense of using more energy due to more muscle contraction [212]. The result is lower chances of fall [210].

For the current experimental setup, subjects were given the information trips will be randomly administered during both the noExo and Exo-assist trials. This knowledge of falls is necessary for ethical reasons. Upon such anticipation, subjects may have consciously adopted more stable postures while walking during both of these experiments. In spite of this, the exosuit is still capable of assisting its user during a trip ($p < 0.001$) when comparing with noExo trials. Hence, this experiment has further validated the efficiency of this exosuit.

Evaluation Process

The current exosuit evaluation relies on established ZMP and XCoM to determine its effectiveness as a fall intervention device. However, it is well known that these balance indicators are not accurate when used on human subjects; given that accurate body models are absent from every individual, and effective normal walking already contains periods of controlled falling. Therefore, the magnitude of these balance indicators cannot be used as an absolute value to judge the subject's state of balance.

Nonetheless, the relative values of these balance indicators can still be used to deduce whether there is a relative loss or gain of stability. In the current evaluation, a significant difference is found between trips and normal trials using the XCoM indicator. The magnitudes of XCoM for the Exo-assist are closer to zero relative to the noExo trials, indicating a gain in stability when the exosuit activates. A XCoM magnitude of zero implies that the subject is standing perfectly still.

Exosuit Design

The current exosuit design mounts its actuator on FIMP before using a Bowden cable to direct forces to the subject's torso (Figure 7.2). In the Exo-assist trip trials, the Bowden cable sheath is attached to the body's anchor point, while it is not attached in the noExo trials. Even though the Bowden cable sheath between FIMP and torso is kept sufficiently long to prevent it from tugging on the subject's body during all trip induced forward torso flexion, it may still have induced a slight backwards force on the subject throughout the entire Exo-assist experiment.

However, the tugging effect should not be observable since the linear velocity of both noExo and Exo-assist trials are similar (Figures 7.7 and 7.8). A pulling Bowden cable sheath would have reduced the forward linear velocity.

7.3 Chapter Conclusion

This chapter evaluated the system performance of the exosuit to assist in fall recovery. The exosuit comprised of a fall detection algorithm, a base-suit and an actuator. The fall inducing movable platform (FIMP) was employed to trigger trips and their corresponding recovery strategy from the subjects.

The actuator of the exosuit was first tested for its effectiveness in assisting in torso extension at different initial flexion angle. The maximum extension generated by the actuator was 6.19 deg at an initial lumbar flexion angle of 15 deg with an output force of 26kg. However, it was observed that the effective torso extension decreased as the initial flexion angle increased and also as the actuator force decreased. The exosuit was therefore configured to use the actuator at 26kg as it can generate the highest lumbar extension.

Subsequently, the exosuit was evaluated using the XCoM and ZMP balance indicator. ZMP that focuses on acceleration did not exhibit any differences between noExo and Exo-assist trials. On the other hand, XCoM that is based on velocity detected significant differences between noExo and Exo-assist trials, on both mid and end-swing trips. This difference between XCoM and ZMP is attributed to the operating characteristics of the actuator, which locked itself to prevent lumbar flexion when activated. XCoM is more suitable as a balance indicator as it better represents the dynamics of an individual. Hence, the exosuit is said to have assisted significantly in balance recovery during both mid and end-swing trips.

In conclusion, the proposed exosuit with all its integrated components is validated as a viable balance assistive device during mid and end-swing trips.

7.4 Future Works

The exosuit is currently only in its infancy stage. It has much to improve in the base-suit design, such as increasing the anchor point stiffness by directing the forces more towards the skeletal structure. The actuator is also too bulky to be worn around as a wearable device. The design and development of a new actuator has already been started. This actuator will likely use a pneumatic muscle with a high pressure cylinder. The air muscle when deflated should allow similar levels of user transparency while providing large force and bandwidth when inflating with a high pressure air inflow. The accuracy of the fall detection algorithm can also be tuned for better performance by adjusting the number of mixtures and hidden states.

More experiments should also be conducted. Firstly, the force versus deformation output relationship has yet to be validated in a dynamical situation. This will be possible with an addition of a strain sensor on the terminal anchor points of the exosuit. The on-timing of FIMP's brake should also be adjusted such that the elevating strategy can be induced in a repeatable manner. The validation of exosuit efficiency should also be re-evaluated when the actuator is made wearable to completely eliminate the effect of the Bowden cable. Finally, the whole experiment should be conducted on the elderly to ensure that the exosuit suits its target audience.

Chapter 8

Conclusion

The increased prevalence of falls, along with its related injuries, in the ageing population amounts to the urgency in developing a solution that can reduce all the associated economic costs. A novel exosuit that intervenes at the onset of fall to prevent fall impact is here proposed. The prevention of fall impacts aids in minimising episodes of hip and arm injuries. Hence, the economic costs associated with taking care of the injured may be significantly reduced. This exosuit creates assistive lumbar extension torques during trips to bring the CoM towards the middle of the BoS. Several components are required to realise the exosuit. These include the pre-impact fall detection, base-suit and actuator. In addition, a fall inducing movable platform (FIMP) is required to induce reliable and repeatable trips for the study and validation of this exosuit's functionality. Figure 8.1 shows the interaction of all the components necessary for the creation of this exosuit.

The pre-impact fall detection algorithm detects fall before triggering the actuator to activate. Here, the actuator activates in 2 stages. The first stage uses a lower force to eliminate the majority of the body compliance, while the second stage induces lumbar extension. The base-suit is made up of commercially available safety harness to transmit forces from the actuator to anchor points on the body. Concurrently, the FIMP uses a follow-me algorithm to allow subjects to perform overground walking while detecting their gait phases. FIMP will then activate the fall mechanisms to induce the corresponding fall at the correct gait phase upon the command of the investigators. A total of 5 main contributions can be identified from the realisation of the exosuit:

Figure 8.1: Exosuit and FIMP components. FIMP is responsible for inducing falls upon the subjects during overground walking. The exosuit, with its fall detection capabilities, will independently detect a fall and initiate the actuator to assist in balance recovery. The base-suit is a body-worn webbing system that directs actuator forces to the anchor points on the subject's body.

Accurate real-time near-fall detection

The fall detection algorithm implements conventional HMM differently. Normally, one HMM is required for every motion type, but the current implementation uses a single HMM for all ADLs. Falls are then detected as anomalies when HMM outputs a low probability. The chosen HMM model takes in accelerometer and gyroscope inputs from 3 IMUs, 1 on the torso and 2 on the thighs. Evaluation results from 18 subjects show that a sensitivity of 90.4% and precision of 87.4% can be achieved, with an average detection latency (the period from fall onset to detection) of 128.21ms. The system functions in real-time on a raspberry pi SBC. Although the current algorithm has only been validated on self-balancing motion and trips, more motion can be included by merely adding the motion into the HMM during training.

Novel method of estimating body compliance

The efficiency of an exosuit depends significantly on the base-suit to create high stiffness anchor points. However, the dependency of lumbar flexion on applied stress and strain causes inaccuracy when evaluating the exosuit stiffness. Hence, a new method of decoupling force and strain measurement is proposed. The method involves keeping the strain constant while measuring force and vice-versa. Thereafter, a simple feed-forward neural network is employed to estimate the force output based on required strain and body parameters. The experimental results showed

that the network had an average residual of $7.556N$, which was 33% lower than the next better performing model. Additionally, this network has determined that the trunk skeletal muscle, shoulders and visceral fat are the three most critical factors in affecting the exosuit stiffness.

High Stroke, High Bandwidth, High Force and High Transparency Actuator

The torso has been previously identified to be the most effective body part to actuate during fall recovery. Here, a torso actuator has been created to target torso extension. The novelty of the actuator lies in its two-stage stroke design ($550cm$), with a high bandwidth ($3m/s$), high force ($184N$) and high transparency. The first stage of the stroke uses a lower strength constant force spring that is directed at reducing the compliance of the system. Subsequently, the second stage uses more force to actuate the bulky torso. In this manner, the total achieved stroke can be much higher, and the majority of the force output is spent on actuating torso extension. The force generating components are also decoupled from the user through the use of cam cleats, giving the user freedom of movement. However, the weight and size of this actuator can be further reduced.

Overground fall inducing movable platform

An overground fall inducing movable platform (FIMP) is necessary for the study of falls and exosuit validation. It includes a subject follower, gait phase detection algorithm and fall inducing mechanisms. The subject follower enables overground walking, which is critical in replicating true fall scenarios. On the other hand, the gait phase detection algorithm induces fall at the correct gait phase, resulting in different recovery strategies to emerge. It is shown that the gait phase can be extracted by using the bandpass filtered thigh flexion angle and flexion velocity. Upon bandpass filtering the flexion angles, the offset caused by changing gait patterns was removed and the periodicity of the extracted phase angle showed significant improvements. Subsequently, the filtered signals are fitted to a unit sine wave using the Levenberg Marquardt algorithm, that allows consistent phase detection even when gait pattern changes.

The fall inducing mechanisms of the FIMP induces trips and slips by using an electromagnetic brake and a DC motor respectively. The brake and motor are attached to the ankle of the subject through a wire rope which was kept slightly taut by power springs, allowing for instantaneously force transfer. During trips, the brake

will activate at either the mid-swing phase or the end-swing phase. This induces a sudden deceleration of the ankle, mimicking a real-world trip. The experimental results reflected that end-swing phase generated the well-known lowering strategy. Interestingly, the mid-swing trips created a skipping strategy that was previously undocumented. This skipping strategy was likely due to the brake activation timing, which held on to the ankle for the entire recovery duration. It accurately mimicked the scenario when the leg encounters an insurmountable obstacle like a high curb, or when the leg gets tangled by a rope.

On the contrary, during slips, the DC motor will turn, pulling the ankle forward and away from the CoM at the end of the swing phase (at touchdown). This will, in turn, induce a sudden acceleration of the ankle, mimicking slipping over a slippery surface during touchdown. However, the evaluation of the slipping response has not been conducted for inclusion in this thesis.

A novel near-fall balance recovery exosuit

Finally, the various exosuit components and FIMP are integrated and tested as a whole. Only forward trip falls were used in the evaluation of the exosuit. Extrapolated centre of mass (XCoM) has been chosen as the balance indicator of choice to evaluate the exosuit. Significance was found with the XCoM indicator when comparing between trials with and without exosuit assistance. This implies that the exosuit can provide sufficient and useful balance recovery assistance to the user during a trip. This also validated the hypothesis that an exosuit is capable of assisting in balance recovery after a fall-onset. However, the exosuit design is not limited to the current implementation as more work can be done to improve the functionality of the exosuit significantly.

To the best of the author's knowledge, this exosuit system is the first of its kind that can perform trip fall assisted recovery. It is also the first system that has shown that assisting the user in the torso during a trip can assist in balance recovery. The potential impact of the exosuit is significant to the elderly population if the exosuit can be made light and wearable. The elderly will be able to more confidently navigate environments without fall prevention solutions while remaining discrete about requiring an assistive device. This confidence may lead to more exercise, which may likely slow down the process of ageing and significantly improve their quality of life.

With reference to the objectives listed in the Introduction (Chapter 1), the following objectives were achieved:

1. A HMM-based real-time near-fall detection algorithm with 90.4% sensitivity and 87.4% precision.
2. A high bandwidth ($3m/s$), high force($184N$), large stroke($550cm$) and low powered actuator.
3. A soft exosuit made using commercial torso and seat harness was characterised. A method of estimating force versus strain output of the exosuit was developed.
4. Gait phase identification algorithm using a bandpass filter and Levenberg Marquardt algorithm.
5. A fall inducing movable platform capable of inducing trip and slip while allowing transparent overground walking for the subjects.
6. The integrated exosuit was evaluated, showing that it is capable of providing balance recovery during trips.

8.0.1 Transitioning to the Elderly Population

The targeted population of the exosuit is the elderly with a BBS score between 21 to 40. These individuals have weaker muscles and joints with slower response time [18–20], which questions the applicability of the exosuit. Since the exosuit is made up of several components, the implications of each component will be discussed separately.

Fall detection system

The first component of the exosuit is the fall detection algorithm and its accompanying sensing modalities. The finalised IMU placement is on the torso and thighs, which allows for easy concealment if the elderly wish to do so. These IMUs require very little electrical power, and a single lightweight $5AH$ battery should run them for more than a day. On the other hand, the SBC requires significantly more power, and the $5AH$ battery will only last the elderly for half a day. Charging the battery during midday create lapse in monitoring of the elderly, which increases the risk of fall impacts. Hence, the finalised sensing algorithm should be implemented on a low-power Field Programmable Gate Arrays (FPGA) device which will significantly lengthen the operating duration of the fall detection system. Recharging only needs to be done every night when users are safe on the bed.

Falls sustained by the elderly are also likely to be slower, with more directional variability than healthy subjects. The slower and higher variability of fall will lead to a fewer disparity between dynamics of falls and ADLs, which may hinder the accuracy of the fall detection algorithm. In this scenario, the random forest approach [213] may be employed to increase detection accuracy. This approach includes training multiple models for fall detection and averaging the output of all the models to obtain higher accuracy. The computational latency of implementing the random forest approach must be taken into account as multiple models must be computed simultaneously. Although the implementation of the algorithms onto the FPGA could be useful in increasing computational speed. The fall detection accuracy based on the elderly's gait must first be tested on the current algorithm before more work should be done on changing the detection algorithm.

Base-suit and Actuator

The base-suit creates anchor points on the subjects to direct forces from the actuators. When the base-suit is worn on the elderly, its apparent stiffness will most likely decrease, as the elderly are likely to have weaker and smaller muscles. Since the webbing materials used in the base-suit are already high in stiffness, the alternatives are to increase the actuator stroke or to increase the subject's body stiffness. Actuator stroke adjustments are easy with the current design, but its customizability increases its weight and size, making it non-wearable. Pneumatic muscles with a high-pressure gas cylinder can be used to store enough energy for a single fall intervention. Much like the activation of the current actuator that only requires energising the electromagnets for a split second, the pressurised gas cylinder will require refuelling only after activation. Therefore, it will require minimal intervention from the users or caregivers until a fall has been detected. Given that a fall happens at a rate of 0.65 times annually, refuelling will not be a big hassle.

The proposed solution to increasing the body stiffness is to use an airbag that inflates inside the base-suit webbing at the instance when a fall is detected. The inflated base-suit will wrap around the user, increasing its stiffness before the actuator activates and provide assistive forces. It can be used in tandem with the high-pressure air-cylinder for the pneumatic muscles.

The actuator requirement for the elderly will also be different. Since the elderly falls at a slower speed, they should require lesser assistive forces to arrest the induced unwanted momentum. However, the elderly who falls at lower speed are

also those who have weaker muscles, because they walk slower. These individuals that are weaker will then require more assistance than healthy subjects. Hence, the amount of assistive force depends on the physical condition of the user.

Overall Acceptance

An ideal exosuit for use by the elderly, should be accurate, lightweight, non-obtrusive, and require minimal maintenance. In addition, this exosuit should also be completely hidden under their clothes as they might not want to be thought of as weaker members of the society.

Thus, the exosuit should be as compact as possible. Although the current exosuit has yet to come close to the ideal, this thesis has revealed promising results and provided clear future directions to aid the expansion of the exosuit's potential to its maximum.

Appendix A

Quaternion to YXZ Euler Angle conversion

The YXZ rotation order is the preferred system rotation order because, given the OpenGL coordinate system used in our project (+ X pointing to the right, + Y straight up and + Z towards the viewer), most of the motion will be along the Y and X axis. When subjects turn their entire body to change their heading angle, that angle will predominantly be reflected in the Y -axis value if we use any rotation order that starts with Y axis first (Y^{**} , $*$ represent any axis). Wrapping angle problem in the Y -axis will not affect any of the algorithms used in the project because they will be negated when constraining the heading angle, as stated in 3.4.1. The next predominant rotation axis will be the X -axis, as most human motion are within the sagittal plane. Angles extracted by the YX^{*} rotation will reflect most of the remaining rotations from the human body. Wrapping angles are rarely seen in X -axis as subjects are rarely required to rotate their hands and legs more than 180 degrees from the global coordinate system. The last axis is chosen to be the Z -axis to reduce interference with the first Y -axis during quaternion-Euler conversion.

To convert a quaternion to Euler angles using YXZ rotation order, we use the following code

```
double test = y*z - w*x;
if (test > 0.45) // singularity at north pole
{
    Rot_y = -2 * atan2(z, w);
    Rot_x = -M_PI / 2;
    Rot_z = 0;
}
```

```

else if (test < -0.45) { // singularity at south pole
Rot_y = 2 * atan2(z, w);
Rot_x = M_PI / 2;
Rot_z = 0;
}
else {
Rot_y = atan2((2*x*z+2*w*y), (w^2-x^2-y^2+z^2))
Rot_x = asin(-2(y*z-w*x))
Rot_z = atan2((2*x*y+2*w*z), (w^2-x^2+y^2-z^2))
}

```

where w, x, y, z are the components of the quaternion and M_{PI} is 3.14159. Rot_x , Rot_y and Rot_z are rotation around the x , y and z axes respectively. Singularities happened because of gimbal lock.

If the IMUs are orientated such that their ports are always facing the ground, then the YZX rotation order might be able to reduce more of the wrapping angle problem. The code for quaternion to YZX rotation is as follows:

```

double test = x*y + z*w;
if (test > 0.45) { // singularity at north pole
Rot_y = 2 * atan2(x, w);
Rot_z = M_PI/2;
Rot_x = 0;
}
else if (test < -0.45) { // singularity at south pole
Rot_y = -2 * atan2(x, w);
Rot_z = - M_PI/2;
Rot_x = 0;
}
else {
Rot_y = atan2(2*y*w-2*x*z, 1 - 2*y^2 - 2*z^2);
Rot_z = asin(2*test);
Rot_x = atan2(2*x*w-2*y*z, 1 - 2*x^2 - 2*z^2);
}

```

Appendix B

ROC Curves for AngMom Fall Detection

ROC of AngMom about the CoM being used as a fall detection algorithm (Figure B.1). An AUC of 0.502 indicates that AngMom about CoM is not suitable as an accurate fall detector. A model with random classification will have an AUC of 0.5.

Figure B.1: The ROC curves (solid red) showing the accuracy of AngMom about the CoM as a fall detection algorithm. The red shaded cloud represents maximum and minimum TPR at every FPR samples. The red dotted line shows the standard deviation of TPR at their corresponding FPR.

Additionally, the AUC of both the AngMom calculated about the right (Figure B.2) and left ankle (Figure B.3) are at 0.549 and 0.573 respectively. These AUC values are not significantly higher from the random classification model of 0.5 as well.

ROC Curves of AngMom about Right Ankle

Figure B.2: The ROC curves (solid red) showing the accuracy of AngMom about the right ankle as a fall detection algorithm. The red shaded cloud represents maximum and minimum TPR at every FPR samples. The red dotted line shows the standard deviation of TPR at their corresponding FPR.

ROC Curves of AngMom about Left Ankle

Figure B.3: The ROC curves (solid red) showing the accuracy of AngMom about the left ankle as a fall detection algorithm. The red shaded cloud represents maximum and minimum TPR at every FPR samples. The red dotted line shows the standard deviation of TPR at their corresponding FPR.

Appendix C

ROC Curves for HMM Fall Detection

The 15 HMM datasets from Table 3.2 in Section 3.6 is shown in Figure C.1. For each dataset, the ROC curve is plotted and its AUC is shown at its bottom left corner. A higher AUC indicates that the HMM dataset and its corresponding trained HMM is a better model at predicting the positive class.

Although the AUC of all ROC curves are above 0.97, indicating a highly accurate model, it is known that ROC curves are susceptible to results skewing when there is a large imbalance in observations. In this experiment, the number of ADLs greatly outnumber the number of collected falls. This imbalance of observations causes specificity ($TN/(TN + FP)$) to be always high, leading to a much higher AUC [184]. Hence, Section 3.6 uses Precision-Recall curves to determine the best model. PR curves uses precision ($TP/(TP + FP)$) over sensitivity ($TP/(TP + FN)$) to avoid the true negative (TN) term.

ROC for all 15 combinations of HMM datasets

Figure C.1: The ROC curves (solid red) for each of the 15 HMM datasets. The red shaded cloud represents maximum and minimum TPR at every FPR samples. The blue dotted line shows the standard deviation of TPR at their corresponding FPR. AG = Accelerometer and Gyroscope; AGO2 = Accelerometer, Gyroscope, Yaw and Pitch; AGO3 = Accelerometer, Gyroscope, Roll, Yaw and Pitch; AGD = Accelerometer, Gyroscope and 3 axis direction vector; AGQ = Accelerometer, Gyroscope and Quaternion. The HMM which uses dataset 13 shows the highest AUC at 0.988, while dataset 6 and 15 shows the next highest AUC at 0.986.

Appendix D

PR Curves for Individual HMM Fall Detection

This appendix shows the individual PR curves for each of the 18 subjects' HMM datasets as mentioned in Section 3.3 and 3.6. The jaggedness of the PR curves occurs because the number of true positives does not increase with increasing false negatives.

PR Curves for Subject 1 datasets with 4 sliding window

Figure D.1: Subject 1's PR curves (solid red) for each of the 15 HMM datasets. AG = Accelerometer and Gyroscope; AGO2 = Accelerometer, Gyroscope, Yaw and Pitch; AGO3 = Accelerometer, Gyroscope, Roll, Yaw and Pitch; AGD = Accelerometer, Gyroscope and 3 axis direction vector; AGQ = Accelerometer, Gyroscope and Quaternion.

PR Curves for Subject 2 datasets with 4 sliding window

Figure D.2: Subject 2's PR curves (solid red) for each of the 15 HMM datasets. AG = Accelerometer and Gyroscope; AGO2 = Accelerometer, Gyroscope, Yaw and Pitch; AGO3 = Accelerometer, Gyroscope, Roll, Yaw and Pitch; AGD = Accelerometer, Gyroscope and 3 axis direction vector; AGQ = Accelerometer, Gyroscope and Quaternion.

PR Curves for Subject 3 datasets with 4 sliding window

Figure D.3: Subject 3's PR curves (solid red) for each of the 15 HMM datasets. AG = Accelerometer and Gyroscope; AGO2 = Accelerometer, Gyroscope, Yaw and Pitch; AGO3 = Accelerometer, Gyroscope, Roll, Yaw and Pitch; AGD = Accelerometer, Gyroscope and 3 axis direction vector; AGQ = Accelerometer, Gyroscope and Quaternion.

PR Curves for Subject 4 datasets with 4 sliding window

Figure D.4: Subject 4's PR curves (solid red) for each of the 15 HMM datasets. AG = Accelerometer and Gyroscope; AGO2 = Accelerometer, Gyroscope, Yaw and Pitch; AGO3 = Accelerometer, Gyroscope, Roll, Yaw and Pitch; AGD = Accelerometer, Gyroscope and 3 axis direction vector; AGQ = Accelerometer, Gyroscope and Quaternion.

PR Curves for Subject 5 datasets with 4 sliding window

Figure D.5: Subject 5's PR curves (solid red) for each of the 15 HMM datasets. AG = Accelerometer and Gyroscope; AGO2 = Accelerometer, Gyroscope, Yaw and Pitch; AGO3 = Accelerometer, Gyroscope, Roll, Yaw and Pitch; AGD = Accelerometer, Gyroscope and 3 axis direction vector; AGQ = Accelerometer, Gyroscope and Quaternion.

PR Curves for Subject 6 datasets with 4 sliding window

Figure D.6: Subject 6's PR curves (solid red) for each of the 15 HMM datasets. AG = Accelerometer and Gyroscope; AGO2 = Accelerometer, Gyroscope, Yaw and Pitch; AGO3 = Accelerometer, Gyroscope, Roll, Yaw and Pitch; AGD = Accelerometer, Gyroscope and 3 axis direction vector; AGQ = Accelerometer, Gyroscope and Quaternion.

PR Curves for Subject 7 datasets with 4 sliding window

Figure D.7: Subject 7's PR curves (solid red) for each of the 15 HMM datasets. AG = Accelerometer and Gyroscope; AGO2 = Accelerometer, Gyroscope, Yaw and Pitch; AGO3 = Accelerometer, Gyroscope, Roll, Yaw and Pitch; AGD = Accelerometer, Gyroscope and 3 axis direction vector; AGQ = Accelerometer, Gyroscope and Quaternion.

PR Curves for Subject 8 datasets with 4 sliding window

Figure D.8: Subject 8's PR curves (solid red) for each of the 15 HMM datasets. AG = Accelerometer and Gyroscope; AGO2 = Accelerometer, Gyroscope, Yaw and Pitch; AGO3 = Accelerometer, Gyroscope, Roll, Yaw and Pitch; AGD = Accelerometer, Gyroscope and 3 axis direction vector; AGQ = Accelerometer, Gyroscope and Quaternion.

PR Curves for Subject 9 datasets with 4 sliding window

Figure D.9: Subject 9's PR curves (solid red) for each of the 15 HMM datasets. AG = Accelerometer and Gyroscope; AGO2 = Accelerometer, Gyroscope, Yaw and Pitch; AGO3 = Accelerometer, Gyroscope, Roll, Yaw and Pitch; AGD = Accelerometer, Gyroscope and 3 axis direction vector; AGQ = Accelerometer, Gyroscope and Quaternion.

PR Curves for Subject 10 datasets with 4 sliding window

Figure D.10: Subject 10's PR curves (solid red) for each of the 15 HMM datasets. AG = Accelerometer and Gyroscope; AGO2 = Accelerometer, Gyroscope, Yaw and Pitch; AGO3 = Accelerometer, Gyroscope, Roll, Yaw and Pitch; AGD = Accelerometer, Gyroscope and 3 axis direction vector; AGQ = Accelerometer, Gyroscope and Quaternion.

PR Curves for Subject 11 datasets with 4 sliding window

Figure D.11: Subject 11's PR curves (solid red) for each of the 15 HMM datasets. AG = Accelerometer and Gyroscope; AGO2 = Accelerometer, Gyroscope, Yaw and Pitch; AGO3 = Accelerometer, Gyroscope, Roll, Yaw and Pitch; AGD = Accelerometer, Gyroscope and 3 axis direction vector; AGQ = Accelerometer, Gyroscope and Quaternion.

PR Curves for Subject 12 datasets with 4 sliding window

Figure D.12: Subject 12's PR curves (solid red) for each of the 15 HMM datasets. AG = Accelerometer and Gyroscope; AGO2 = Accelerometer, Gyroscope, Yaw and Pitch; AGO3 = Accelerometer, Gyroscope, Roll, Yaw and Pitch; AGD = Accelerometer, Gyroscope and 3 axis direction vector; AGQ = Accelerometer, Gyroscope and Quaternion.

PR Curves for Subject 13 datasets with 4 sliding window

Figure D.13: Subject 13's PR curves (solid red) for each of the 15 HMM datasets. AG = Accelerometer and Gyroscope; AGO2 = Accelerometer, Gyroscope, Yaw and Pitch; AGO3 = Accelerometer, Gyroscope, Roll, Yaw and Pitch; AGD = Accelerometer, Gyroscope and 3 axis direction vector; AGQ = Accelerometer, Gyroscope and Quaternion.

PR Curves for Subject 14 datasets with 4 sliding window

Figure D.14: Subject 14's PR curves (solid red) for each of the 15 HMM datasets. AG = Accelerometer and Gyroscope; AGO2 = Accelerometer, Gyroscope, Yaw and Pitch; AGO3 = Accelerometer, Gyroscope, Roll, Yaw and Pitch; AGD = Accelerometer, Gyroscope and 3 axis direction vector; AGQ = Accelerometer, Gyroscope and Quaternion.

PR Curves for Subject 15 datasets with 4 sliding window

Figure D.15: Subject 15's PR curves (solid red) for each of the 15 HMM datasets. AG = Accelerometer and Gyroscope; AGO2 = Accelerometer, Gyroscope, Yaw and Pitch; AGO3 = Accelerometer, Gyroscope, Roll, Yaw and Pitch; AGD = Accelerometer, Gyroscope and 3 axis direction vector; AGQ = Accelerometer, Gyroscope and Quaternion.

PR Curves for Subject 16 datasets with 4 sliding window

Figure D.16: Subject 16's PR curves (solid red) for each of the 15 HMM datasets. AG = Accelerometer and Gyroscope; AGO2 = Accelerometer, Gyroscope, Yaw and Pitch; AGO3 = Accelerometer, Gyroscope, Roll, Yaw and Pitch; AGD = Accelerometer, Gyroscope and 3 axis direction vector; AGQ = Accelerometer, Gyroscope and Quaternion.

PR Curves for Subject 17 datasets with 4 sliding window

Figure D.17: Subject 17's PR curves (solid red) for each of the 15 HMM datasets. AG = Accelerometer and Gyroscope; AGO2 = Accelerometer, Gyroscope, Yaw and Pitch; AGO3 = Accelerometer, Gyroscope, Roll, Yaw and Pitch; AGD = Accelerometer, Gyroscope and 3 axis direction vector; AGQ = Accelerometer, Gyroscope and Quaternion.

PR Curves for Subject 18 datasets with 4 sliding window

Figure D.18: Subject 18's PR curves (solid red) for each of the 15 HMM datasets. AG = Accelerometer and Gyroscope; AGO2 = Accelerometer, Gyroscope, Yaw and Pitch; AGO3 = Accelerometer, Gyroscope, Roll, Yaw and Pitch; AGD = Accelerometer, Gyroscope and 3 axis direction vector; AGQ = Accelerometer, Gyroscope and Quaternion.

Appendix E

Circuit Design

The trip and slip system for the overground platform are shown here. The trip uses a brake from *MIKI Pulley* (111-10-11G 24V 25DIN) with 20Nm dynamic friction torque and 22Nm static friction torque. Slip uses a DC motor from *XaJong Co. Ltd* (M35SWG-2436), with a continuous torque of 1Nm and speed of 3600rpm.

E.1 Trip Circuit

Figure E.1: Circuit for activating a brake using a 5V or 3.3V microcontroller. Controller requires a active low to activate brake.

E.2 Slip Circuit

Figure E.2: Circuit for activating a DC motor using a 5V or 3.3V microcontroller. Controller requires a active low to activate motor.

Appendix F

Bandpass Filter

High order band-pass filter is created by combining low-pass and high-pass filters. A single low-pass filter can be easily created using the following equation:

$$y[i] = \alpha * x[i] + (1 - \alpha) * y[i - 1] \quad (\text{F.1})$$

where $y[i]$ and $y[i - 1]$ are the current timestamp and previous timestamp filtered output respectively; $x[i]$ is the current timestamp unfiltered data. α is the smoothing factor calculated through:

$$\alpha = \frac{2\pi\Delta t f_c}{2\pi\Delta t f_c + 1} \quad (\text{F.2})$$

where Δt is the time sample interval and f_c is the cutoff frequency.

High-pass filter is created using the following equations:

$$y[i] = \beta * y[i - 1] + \beta * (x[i] - x[i - 1]) \quad (\text{F.3})$$

$$\beta = \frac{1}{2\pi\Delta t f_c + 1} \quad (\text{F.4})$$

A 2nd order band-pass filter is created by using 2 low-pass and 2 high-pass filters. The output from the previous filter is substituted into the next filter as its current input ($x[i]$) until all 4 filters are used.

Appendix G

Components Specification

G.1 Inertial Measurement Unit (Figure G.1)

Figure G.1: 3-Space™ USB/RS232 IMUs obtained from *Yost Labs*

Name: 3-Space™ Sensor USB/RS232 IMU

Brand: Yost Labs

Model: TSS-USB-S

Dimensions: 35mm X 50mm X 15mm

Weight: 17grams

Supply Voltage: +5v USB, +3.3V +6.0V external jack

Communication Interfaces: USB 2.0, RS232 Asynchronous Serial

Filter update Rate: Up to 250Hz with Kalman AHRS, Up to 850Hz with QCOMP AHRS, Up to 1350Hz with IMU mode

Orientation output: absolute & relative quaternion, Euler angles, axis angle, rotation matrix

Other outputs: raw sensor data, normalized sensor data, calibrated sensor data, temperature

Shock survivability: 5000g

Temperature range: -40°C to 85°C

G.2 Chest Harness Specifications (Figure G.2)

Figure G.2: Chest harness used in exosuit

Name: Skill Chest Harness

Brand: Rock Empire

Model: OUC003

Test Standard: EN 361

Dynamic Test description: The harness is fitted to a 100kg solid torso dummy and connected via the harness attached to a 2-metre length of 11mm mountaineering rope (specifically chosen to generate a known force to the harness in the case of a fall). This rope is attached to a solid anchor point, and the dummy released over a distance of 4 metres. This test is carried out twice on

each harness attachment, once from a head-up position, once from a head-down position (i.e. with the dummy upside down on release). To pass the test, the harness must hold the dummy following both drops, with the dummy held in a position not exceeding 50° from the upright position. These tests are repeated on every attachment point on a harness.

Static Test description: Whole products are subjected to tensile tests, based on a factor of safety on the 6kN expected in use. Harnesses are subject to a 15kN tensile force applied in the upward direction, followed by a 10kN force applied downward. Lanyards are subjected to either 22kN or 15kN applied between the attachment points, depending on the material used – an increased force as the lanyard is expected to be more exposed to ageing factors such as abrasion in use. Tensile forces are usually applied and held for at least 3 minutes, to ensure the breaking strength of the product is more than the force specified by the standard.

Corrosion Resistance Test description: Metallic components used in fall protection equipment are subjected to a neutral salt-spray test intended to prove a minimum resistance to environmental corrosion (rust). Products are held within a sealed chamber, which is filled with a salt-water mist, which can induce rust in unprotected metals. Products are subjected to either 24 or 48 hours exposure and examined for rusting and function afterwards.

G.3 Sit Harness Specifications (Figure G.3)

Name: Speedy Sit Harness

Brand: Rock Empire

Model: VUG005

Test Standard: EN 12277

Waist Belt Test description: Attach the waist-belt between two bars (diameter 20 mm). Apply a force increasing gradually to 1+0.1kN over a period 1+/-0.25min. Mark the strap at the outer edge of the buckle. Then increase the force gradually to 10 +0.1kN over a period of 2+/-0.25 min. Hold this load for 3+/-0.25min. After release mark the strap again at the outer edge of the

Figure G.3: Sit harness used in exosuit

buckle. Unfasten the buckle and measure the distance between the two marks. Maximum distance allowed is 20 mm.

Static Test description: Place an upright test dummy in the harness. Apply a force of $0.8 \pm 0.1 \text{ kN}$ and mark the position of the buckle. Apply a force increasing gradually to $15 \pm 0.3 \text{ kN}$ over a period $2 \pm 0.25 \text{ min}$. Hold this load for $1 \pm 0.25 \text{ min}$ and then release the tension completely over a maximum of 1 min. Reapply the force and increase gradually to $15 \pm 0.3 \text{ kN}$ and hold it for $3 \pm 0.25 \text{ min}$. Mark the position of the buckle. Measure the distance between the two marks. Maximum distance allowed is 20 mm.

G.4 Sphygmomanometer Specifications (Figure G.4)

Name: Premium Infant Aneroid Sphygmomanometer

Brand: Prestige Medical

Model: 82-INF

Resolution: 0 - 300mmHg

Figure G.4: Infant sphygmomanometer used for exosuit fitting measurement

G.5 Force Gauge Specifications (Figure G.5)

Figure G.5: Force gauge used for all force measurements in this project

Name: Digital 50kg Push-pull force gauge

Brand: ZhiQu

Model: HP-500

Maximum Load: 500N

Resolution: 0.1N

Accuracy: $\pm 0.5\%$

G.6 Weighing Scale Specifications (Figure G.5)

Figure G.6: Weighing scale used for body parameters measurement in exosuit compliancy test

Name: Body composition monitor

Brand: Omron

Model: HBF-375

Functions: Weight, BMI, Segmental (Full Body, Trunk, Legs and Arms) Subcutaneous Fat and Skeletal Muscle Percentage

Weight Accuracy: $\pm 400\text{g}$ (0 to 40kg), $\pm 1\%$ (40.1kg to 135kg)

Fat measurement method: Bioelectrical Impedance Analysis method [214]. It has an error of about $\pm 4\%$ to 6% [215].

Appendix H

Fitting Procedure

This is the detailed description for measuring the fitness of the exosuit.

1. Sphygmomanometer is calibrated by placing a 500N weight on top of the air-pack (Figure H.1). Ensure that pressure is at 10mmHg. The weight is used to reduce the amount of air in the air pack needed to reach a readable value of the pressure sensor. Without the weight, the air pack will be too large to put under the harness straps.

Figure H.1: Calibration of sphygmomanometer using a 500N weight

2. Request subject to wear both the chest loosely.
3. Tighten the chest straps around the chest harness, keeping the shoulder straps loose.
 - (a) Before fully tightening the chest strap, place air pack under the chest strap at the right side of the ribcage (under armpit, Figure H.2).

Figure H.2: Placement of air pack under armpit for measuring chest strap fitting

- (b) Ensure that the middle of the chest strap is located at the sternum.
 - (c) Ask subject to breathe out and hold his breath, while both his feet are together. This is very important to ensure repeatability.
 - (d) Adjust the tightness of the strap such that the pressure gauge reading is within the suggested range. Record the reading.
4. Repeat step 3 for the left shoulder straps (Figure H.3).

Figure H.3: Placement of air pack on the left shoulder for measuring shoulder strap fitting

5. Repeat step 3 for the right shoulder straps.

6. Proceed on to the sit harness. Start by asking subject to wear the sit harness loosely.
7. Repeat step 3 for the waist strap by placing the air pack at the left iliac crest, while leaving the thigh straps loose (Figure H.4).

Figure H.4: Placement of air pack on the left iliac crest for measuring waist strap fitting

8. Repeat step 3 for left thigh straps. Place the air pack along the intersection of front and back thigh straps (Figure H.5).

Figure H.5: Placement of air pack on the left iliac crest for measuring waist strap fitting

9. Repeat step 3 for right thigh straps.

Appendix I

Decoupled Force and Deformation measurement for stiffness calculation

I.1 Decoupled Force measurement

1. Begin by ensuring the subject's heel and hips are in a vertical position (90 deg). Make use of a helper surface such as strapping the knees of the subject to the vertical beam of a Table (Figure I.1).

Figure I.1: Ensure subject's heel and hips are completely vertical by aligning with a vertical structure

2. Provide a movable chair for the subject to keep their balance as they perform torso flexion.
3. Hook the cable from the actuator to the force sensor

4. Before taking any readings, the subject should perform torso flexion to 30 deg and hold for 5 seconds before returning to 90 deg. This is to ensure all slackness in the exosuit are all removed and concentrated on the cable.
5. Adjust the length of the cable such that a force reading of 10N is obtained in the vertical position.
6. Request subject to perform torso flexion at 5 deg decrements until 30 deg is reached. Record force output at each increment.

I.2 Decoupled Deformation measurement

1. Begin by ensuring the subject's heel and hips are in a vertical position (90 deg). Make use of a helper surface such as strapping the knees of the subject to the vertical beam of a Table (Figure I.1).
2. Provide a movable chair for the subject to keep their balance as they perform torso flexion.
3. Hook the cable from the actuator to the force sensor
4. Before taking any readings, the subject should perform torso flexion to 30 deg and hold for 5 seconds before returning to 90 deg. This is to ensure all slackness in the exosuit are all removed and concentrated on the cable.
5. Adjust the length of the cable such that a force reading of 10N is obtained in the vertical position.
6. Request subject to perform torso flexion at 5 deg decrements until 30 deg is reached.
7. At each decrement, loosen the cable until the same force reading of 10N is obtained. Measure the length of the cable at each decrement.

Appendix J

Circuit Diagram for Exosuit and FIMP

The whole circuit of all exosuit components and FIMP (Fall inducing movable platform) are shown in FigureJ.1.

The circuit comprises the following segments.

1. 5 switches at the top left
2. Slip, Trip and Actuator circuit
3. Arduino
4. Latte Panda
5. Sabertooth Motor Driver
6. Raspberry Pi
7. Analog to Digital Converter (ADC)

4 out of the 5 switches are push switches that allow for investigators to test FIMP (Slip and Trip buttons) and the actuator (Stage 1 and 2) functionalities. The last master switch is used to initiate the gait phase detection on the micro-controller, which will induce a trip or slip when the appropriate gait phase has been detected.

The circuit used for trip is shown in FigureE.1 while slip is shown in FigureE.2. Stage 1 and Stage 2 uses the similar circuit as FigureE.1, except the brake and kick-back diode are changed to a normally energized electromagnet.

An Arduino Uno Rev 3 is used. It is powered by a 10AH, 1.5A output power bank via its USB-B input.

Figure J.1: Circuit diagram of the entire exosuit and FIMP system.

On the other hand, Latte Panda 4G/64G is used as the micro-controller for FIMP. Its onboard Arduino Leonardo connects to the Trip and Slip trigger from the standalone Arduino to stop FIMP in the event of fall to allow the trip brakes to have maximum effect on the subject. Intel Realsense Depth Camera D435 is connected to Latte Panda via USB 3.0 Type A for calculation of distance and heading angle of the subject. The speed and direction FIMP is calculated on Latte Panda and sent to Sabertooth motor driver via the Arduino Leonardo pins. A 30AH, 3A power bank is used to power Latte Panda.

Sabertooth 2x32 motor driver is chosen to drive the 2 250W DC motor and brakes. It is configured to Radio Control Mode, using Battery, Mixed mode, Exponential and Microcontroller controlled (0b010100). A 24V, 35AH LiPo battery powers

sabertooth which directs the power to the 2 DC motors and brakes.

Raspberry Pi 3 Model B+ (RPI) is used for connecting the IMUs, Arduino Uno and Analog to Digital Converter (ADC). Fall detection and gait phase calculation are done on RPI, and it is powered by a 20AH 3A power bank.

An Analog to Digital Converter (ADS1115) is used to convert analogue signals from a galvanic skin resistance sensor and a force sensor to digital signal readable by RPI. It is configured to be in continuous mode, no multiplex, gain at 4.096V, 860 SPS(samples per second), and disabled comparator (0b10000010, 0b11100011).

Appendix K

FIMP Transparency for Individuals

Transparency of FIMP describes how FIMP affects the left and right leg kinematics when comparing NormalWalking (NW) and StrapWalking (SW). StrapWalking is the condition where a strap extended from the brake and motor of FIMP is attached to the left leg of the subject. NormalWalking is the condition where no strap is attached to any of the legs. Both NW and SW trials involve walking for 5 times, each with about 4 to 6 strides. The graphs are showing the mean and standard deviation of every individual's stride. The transparency analysis for all the subjects is described in Section 6.3.2.

K.1 Left Leg SPM analysis

Figure K.1: Comparison of Subject 1 NormalWalking (NW) vs StrapWalking (SW) trials for the left leg using SPM.

Figure K.2: Comparison of Subject 2 NormalWalking (NW) vs StrapWalking (SW) trials for the left leg using SPM.

Subject 3 3 Leg t-test (NW vs SW)

Figure K.3: Comparison of Subject 3 NormalWalking (NW) vs StrapWalking (SW) trials for the left leg using SPM.

Subject 4 Left Leg t-test (NW vs SW)

Figure K.4: Comparison of Subject 4 NormalWalking (NW) vs StrapWalking (SW) trials for the left leg using SPM.

Subject 5 4 Leg t-test (NW vs SW)

Figure K.5: Comparison of Subject 5 NormalWalking (NW) vs StrapWalking (SW) trials for the left leg using SPM.

Subject 6 2 Leg t-test (NW vs SW)

Figure K.6: Comparison of Subject 6 NormalWalking (NW) vs StrapWalking (SW) trials for the left leg using SPM.

Subject 7 Left Leg t-test (NW vs SW)

Figure K.7: Comparison of Subject 7 NormalWalking (NW) vs StrapWalking (SW) trials for the left leg using SPM.

K.2 Right Leg SPM analysis

Figure K.8: Comparison of Subject 1 NormalWalking (NW) vs StrapWalking (SW) trials for the right leg using SPM.

Figure K.9: Comparison of Subject 2 NormalWalking (NW) vs StrapWalking (SW) trials for the right leg using SPM.

Subject 3 Right Leg t-test (NW vs SW)

Figure K.10: Comparison of Subject 3 NormalWalking (NW) vs StrapWalking (SW) trials for the right leg using SPM.

Subject 4 Right Leg t-test (NW vs SW)

Figure K.11: Comparison of Subject 4 NormalWalking (NW) vs StrapWalking (SW) trials for the right leg using SPM.

Subject 5 Right Leg t-test (NW vs SW)

Figure K.12: Comparison of Subject 5 NormalWalking (NW) vs StrapWalking (SW) trials for the right leg using SPM.

Subject 6 Right Leg t-test (NW vs SW)

Figure K.13: Comparison of Subject 6 NormalWalking (NW) vs StrapWalking (SW) trials for the right leg using SPM.

Subject 7 Right Leg t-test (NW vs SW)

Figure K.14: Comparison of Subject 7 NormalWalking (NW) vs StrapWalking (SW) trials for the right leg using SPM.

Appendix L

FIMP End-Swing analysis for Individuals

End-swing trip kinematics analysis for individuals is shown in this appendix. NormalWalking (NW), StrapWalking (SW) and EndSwing (ES) trials are compared with each other using ANOVA. Subsequently, post-hoc analysis is conducted between them using t-test with an adjusted p-value. End-swing trials require a strap extended from FIMP's brake and motor to be attached to the left leg. The investigator will then randomly trigger the system to start detecting end-swing and activate the brake to induce an end-swing trip. For every individual, at least 3 end-swing trips were collected. The analysis of end-swing trip for all subjects is described in Section 6.3.3

L.1 Left Leg SPM analysis

The gait cycle that contains the instance of perturbation is extracted and analysed. The ANOVA and post-hoc analysis of each subject's left leg will also be shown here.

Subject 1 Left Leg ANOVA (NW vs SW vs ES)

Figure L.1: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs EndSwing (ES) trials for the left leg of Subject 1 with SPM.

Subject 1 Left Leg Post Hoc (NW vs SW vs ES)

Figure L.2: Posthoc analysis of the EndSwing trip trials for the left leg of Subject 1.

Subject 2 Left Leg ANOVA (NW vs SW vs ES)

Figure L.3: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs EndSwing (ES) trials for the left leg of Subject 2 with SPM.

Subject 2 Left Leg Post Hoc (NW vs SW vs ES)

Figure L.4: Posthoc analysis of the EndSwing trip trials for the left leg of Subject 2.

Subject 3 Left Leg ANOVA (NW vs SW vs ES)

Figure L.5: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs EndSwing (ES) trials for the left leg of Subject 3 with SPM.

Subject 3 Left Leg Post Hoc (NW vs SW vs ES)

Figure L.6: Posthoc analysis of the EndSwing trip trials for the left leg of Subject 3.

Subject 4 Left Leg ANOVA (NW vs SW vs ES)

Figure L.7: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs EndSwing (ES) trials for the left leg of Subject 4 with SPM.

Subject 4 Left Leg Post Hoc (NW vs SW vs ES)

Figure L.8: Posthoc analysis of the EndSwing trip trials for the left leg of Subject 4.

Subject 5 Left Leg ANOVA (NW vs SW vs ES)

Figure L.9: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs EndSwing (ES) trials for the left leg of Subject 5 with SPM.

Subject 5 Left Leg Post Hoc (NW vs SW vs ES)

Figure L.10: Posthoc analysis of the EndSwing trip trials for the left leg of Subject 5.

Subject 6 Left Leg ANOVA (NW vs SW vs ES)

Figure L.11: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs EndSwing (ES) trials for the left leg of Subject 6 with SPM.

Subject 6 Left Leg Post Hoc (NW vs SW vs ES)

Figure L.12: Posthoc analysis of the EndSwing trip trials for the left leg of Subject 6.

Subject 7 Left Leg ANOVA (NW vs SW vs ES)

Figure L.13: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs EndSwing (ES) trials for the left leg of Subject 7 with SPM.

Subject 7 Left Leg Post Hoc (NW vs SW vs ES)

Figure L.14: Posthoc analysis of the EndSwing trip trials for the left leg of Subject 7.

L.2 Right Leg SPM analysis

The right leg's gait cycle that follows immediately after the left leg perturbation is extracted and analysed. The ANOVA and post-hoc analysis of each subject's right leg will also be shown here.

Figure L.15: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs EndSwing (ES) trials for the right leg of Subject 1 with SPM.

Subject 1 Right Leg Post Hoc (NW vs SW vs ES)

Figure L.16: Posthoc analysis of the EndSwing trip trials for the right leg of Subject 1.

Subject 2 Right Leg ANOVA (NW vs SW vs ES)

Figure L.17: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs EndSwing (ES) trials for the right leg of Subject 2 with SPM.

Subject 2 Right Leg Post Hoc (NW vs SW vs ES)

Figure L.18: Posthoc analysis of the EndSwing trip trials for the right leg of Subject 2.

Subject 3 Right Leg ANOVA (NW vs SW vs ES)

Figure L.19: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs EndSwing (ES) trials for the right leg of Subject 3 with SPM.

Subject 3 Right Leg Post Hoc (NW vs SW vs ES)

Figure L.20: Posthoc analysis of the EndSwing trip trials for the right leg of Subject 3.

Subject 4 Right Leg ANOVA (NW vs SW vs ES)

Figure L.21: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs EndSwing (ES) trials for the right leg of Subject 4 with SPM.

Subject 4 Right Leg Post Hoc (NW vs SW vs ES)

Figure L.22: Posthoc analysis of the EndSwing trip trials for the right leg of Subject 4.

Subject 5 Right Leg ANOVA (NW vs SW vs ES)

Figure L.23: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs EndSwing (ES) trials for the right leg of Subject 5 with SPM.

Subject 5 Right Leg Post Hoc (NW vs SW vs ES)

Figure L.24: Posthoc analysis of the EndSwing trip trials for the right leg of Subject 5.

Subject 6 Right Leg ANOVA (NW vs SW vs ES)

Figure L.25: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs EndSwing (ES) trials for the right leg of Subject 6 with SPM.

Subject 6 Right Leg Post Hoc (NW vs SW vs ES)

Figure L.26: Posthoc analysis of the EndSwing trip trials for the right leg of Subject 6.

Subject 7 Right Leg ANOVA (NW vs SW vs ES)

Figure L.27: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs EndSwing (ES) trials for the right leg of Subject 7 with SPM.

Subject 7 Right Leg Post Hoc (NW vs SW vs ES)

Figure L.28: Posthoc analysis of the EndSwing trip trials for the right leg of Subject 7.

Appendix M

FIMP Mid-Swing analysis for Individuals

Mid-swing trip kinematics analysis for every individual is shown in this appendix. NormalWalking (NW), StrapWalking (SW) and MidSwing (MS) trials are compared with each other using ANOVA. Subsequently, post-hoc analysis is conducted between them using t-test with an adjusted p-value. Mid-swing trials require a strap extended from FIMP's brake and motor to be attached to the left leg. The investigator will then randomly trigger the system to start detecting mid-swing and activate the brake to induce a mid-swing trip. For every individual, at least 3 end-swing trips were collected. The analysis of mid-swing trip for all subjects is described in Section 6.3.4

M.1 Left Leg SPM analysis

The gait cycle that contains the instance of perturbation is extracted and analysed. The ANOVA and post-hoc analysis of each subject's left leg will also be shown here.

Subject 1 Left Leg ANOVA (NW vs SW vs MS)

Figure M.1: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs MidSwing (MS) trials for the left leg of Subject 1 with SPM.

Subject 1 Left Leg Post Hoc (NW vs SW vs MS)

Figure M.2: Posthoc analysis of the MidSwing trip trials for the left leg of Subject 1.

Subject 2 Left Leg ANOVA (NW vs SW vs MS)

Figure M.3: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs MidSwing (MS) trials for the left leg of Subject 2 with SPM.

Subject 2 Left Leg Post Hoc (NW vs SW vs MS)

Figure M.4: Posthoc analysis of the MidSwing trip trials for the left leg of Subject 2.

Subject 3 Left Leg ANOVA (NW vs SW vs MS)

Figure M.5: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs MidSwing (MS) trials for the left leg of Subject 3 with SPM.

Subject 3 Left Leg Post Hoc (NW vs SW vs MS)

Figure M.6: Posthoc analysis of the MidSwing trip trials for the left leg of Subject 3.

Subject 4 Left Leg ANOVA (NW vs SW vs MS)

Figure M.7: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs MidSwing (MS) trials for the left leg of Subject 4 with SPM.

Subject 4 Left Leg Post Hoc (NW vs SW vs MS)

Figure M.8: Posthoc analysis of the MidSwing trip trials for the left leg of Subject 4.

Subject 5 Left Leg ANOVA (NW vs SW vs MS)

Figure M.9: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs MidSwing (MS) trials for the left leg of Subject 5 with SPM.

Subject 5 Left Leg Post Hoc (NW vs SW vs MS)

Figure M.10: Posthoc analysis of the MidSwing trip trials for the left leg of Subject 5.

Subject 6 Left Leg ANOVA (NW vs SW vs MS)

Figure M.11: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs MidSwing (MS) trials for the left leg of Subject 6 with SPM.

Subject 6 Left Leg Post Hoc (NW vs SW vs MS)

Figure M.12: Posthoc analysis of the MidSwing trip trials for the left leg of Subject 6.

Subject 7 Left Leg ANOVA (NW vs SW vs MS)

Figure M.13: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs MidSwing (MS) trials for the left leg of Subject 7 with SPM.

Subject 7 Left Leg Post Hoc (NW vs SW vs MS)

Figure M.14: Posthoc analysis of the MidSwing trip trials for the left leg of Subject 7.

M.2 Right Leg SPM analysis

The right leg's gait cycle that follows immediately after the left leg perturbation is extracted and analysed. The ANOVA and post-hoc analysis of each subject's right leg will also be shown here.

Figure M.15: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs MidSwing (MS) trials for the right leg of Subject 1 with SPM.

Subject 1 Right Leg Post Hoc (NW vs SW vs MS)

Figure M.16: Posthoc analysis of the MidSwing trip trials for the right leg of Subject 1.

Subject 2 Right Leg ANOVA (NW vs SW vs MS)

Figure M.17: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs MidSwing (MS) trials for the right leg of Subject 2 with SPM.

Subject 2 Right Leg Post Hoc (NW vs SW vs MS)

Figure M.18: Posthoc analysis of the MidSwing trip trials for the right leg of Subject 2.

Subject 3 Right Leg ANOVA (NW vs SW vs MS)

Figure M.19: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs MidSwing (MS) trials for the right leg of Subject 3 with SPM.

Subject 3 Right Leg Post Hoc (NW vs SW vs MS)

Figure M.20: Posthoc analysis of the MidSwing trip trials for the right leg of Subject 3.

Subject 4 Right Leg ANOVA (NW vs SW vs MS)

Figure M.21: ANOVA comparison of Normal Walking (NW) vs Strap Walking (SW) vs MidSwing (MS) trials for the right leg of Subject 4 with SPM.

Subject 4 Right Leg Post Hoc (NW vs SW vs MS)

Figure M.22: Posthoc analysis of the MidSwing trip trials for the right leg of Subject 4.

Subject 5 Right Leg ANOVA (NW vs SW vs MS)

Figure M.23: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs MidSwing (MS) trials for the right leg of Subject 5 with SPM.

Subject 5 Right Leg Post Hoc (NW vs SW vs MS)

Figure M.24: Posthoc analysis of the MidSwing trip trials for the right leg of Subject 5.

Subject 6 Right Leg ANOVA (NW vs SW vs MS)

Figure M.25: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs MidSwing (MS) trials for the right leg of Subject 6 with SPM.

Subject 6 Right Leg Post Hoc (NW vs SW vs MS)

Figure M.26: Posthoc analysis of the MidSwing trip trials for the right leg of Subject 6.

Subject 7 Right Leg ANOVA (NW vs SW vs MS)

Figure M.27: ANOVA comparison of NormalWalking (NW) vs StrapWalking (SW) vs MidSwing (MS) trials for the right leg of Subject 7 with SPM.

Subject 7 Right Leg Post Hoc (NW vs SW vs MS)

Figure M.28: Posthoc analysis of the MidSwing trip trials for the right leg of Subject 7.

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