Physical human-environment interaction via wearable sensors : motion tracking and localization

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Physical Human-Environment Interaction via Wearable Sensors: Motion Tracking & Localization

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List of Symbols

$SO(3)$ Special Orthogonal Group, for representation of the three-dimensional rotation

$so(3)$ The skew-symmetric matrix associated with Special Orthogonal Group $SO(3)$

$SE(3)$ Special Euclidean Group, for representation of the three-dimensional rigid body transformation

$se(3)$ The twist associated with Special Euclidean Group $SE(3)$

$T_{i,j}$ Relative displacement of frame i with respect to frame $i-1$,
 $T_{i,j} \in SE(3)$

$R_{i,j}$ Relative orientation of frame i with respect to frame $i-1$, $R_{i,j} \in SO(3)$

$p_{i,j}$ Relative position of frame i with respect to frame j

$\hat{s}$ Skew-symmetric matrix of s (3 by 1 vector),
 $\hat{s} \in so(3), so(3) = \{S \in \mathfrak{R}^{3 \times 3}, S^T = -S\}$

$e^{\hat{\xi}_i q_i}$ The twist motion of the joint twist $\hat{\xi}_i$, under a twist angle q_i , $e^{\hat{\xi}_i q_i} \in SE(3)$

f_w The global reference frame

f_i The body frame of body segment i

f_{is} The sensor frame of the sensor on body segment i

T_i The displacement of frame i with respect to global frame, $T_i \in SE(3)$

$\mathbf{R}_i$	The orientation of frame i with respect to global frame, $\mathbf{R}_i \in SO(3)$
$\mathbf{p}_i$	The position of frame i with respect to global frame
$\mathbf{r}_i$	The body segment dimension of body segment i with respect to its body frame
$\mathbf{l}_{i-1,i}$	The position of the origin of frame i , in frame $i-1$
$\boldsymbol{\omega}_{i,f}$	The angular velocity of body segment i in frame f (in global frame when f is absent)
$\boldsymbol{\alpha}_{i,f}$	The angular velocity of body segment i in frame f (in global frame when f is absent)
$\mathbf{v}_{i,f}$	The velocity of body segment i in frame f (in global frame when f is absent)
$\mathbf{a}_{i,f}$	The acceleration of body segment i in frame f (in global frame when f is absent)
$\mathbf{T}_{is}$	The displacement of sensor frame f_{is} with respect to the global frame
$\mathbf{R}_{is}$	The orientation of sensor frame f_{is} with respect to the global frame
$\mathbf{T}_{iM}$	The relative displacement of sensor frame f_{is} with respect to its body frame f_i
$\mathbf{R}_{iM}$	The relative orientation of sensor frame f_{is} with respect to its body frame f_i
$\mathbf{l}_{iM}$	The relative position of sensor frame f_{is} with respect to its body frame f_i

$\mathbf{F}_{i,f}$ The joint reaction force of joint i in frame f (in global frame when f is absent)

$\boldsymbol{\tau}_{i,f}$ The joint torque of joint i in frame f (in global frame when f is absent)

$\mathbf{g}$ Gravitational acceleration.

Φ The bearing angle of the subject with respect to global frame f_w .

σ_x Standard deviation of x

$\mathbf{P}_A$ The vector representing the distal limb location errors (the hands and the feet with the subscript rh , lh , rf , lf denoting the chain of the right hand, the left hand, the right foot and the left foot respectively).

$\mathbf{X}_{all}$ The column vector of the uncertain error parameters for all limbs
 $\mathbf{X}_{all} \in \Re^{69 \times 1}$

$\mathbf{B}_A$ The matrix that maps the uncertain parameters to the location errors of the distal limbs based on the forward kinematic of the human body.

$\mathbf{w}_{k-1}$ White noise of the discrete-time controlled process in a Kalman Filter, and $p(\mathbf{w}) = N(0, \mathbf{Q})$, where $\mathbf{Q}$ is the corresponding covariance matrix of $\mathbf{w}_{k-1}$.

$\mathbf{z}_k$ The measurement in a Kalman Filter

$\mathbf{v}_k$ The white noise of the measurement $\mathbf{z}_k$, and $p(\mathbf{v}) = N(0, \mathbf{R})$, where $\mathbf{R}$ is the corresponding covariance matrix of $\mathbf{v}_k$.

$\mathbf{s}_k$ The stride vector counted from the beginning of the step to the current moment.

$\delta\theta_i$ The angular error of limb i . $\delta\theta_i = [\delta\theta_{xi}, \delta\theta_{yi}, \delta\theta_{zi}]$.

$\delta l_{i,i+1}$ The dimensional error of limb i . $\delta l_{i,i+1} = [\delta x_{i,i+1}, \delta y_{i,i+1}, \delta z_{i,i+1}]$

δa The acceleration error. $\delta a = [\delta a_x, \delta a_y, \delta a_z]^T$.

$\mathbf{a} \times \mathbf{b}$ Cross product of vector $\mathbf{a}$ and $\mathbf{b}$.

$\mathbf{a} \cdot \mathbf{b}$ Inner product of vector $\mathbf{a}$ and $\mathbf{b}$.

$\|\mathbf{a}\|$ The norm of vector $\mathbf{a}$.

In the symbols, matrixes are represented by the uppercase and boldface letter $\mathbf{M}$. Vectors are represented by the lowercase and boldface letter $\mathbf{v}$. Scalars are presented by the standard letter a . There is one exception that the uppercase $\mathbf{F}$ is used to represent the force vector.

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Abstract

Human-environment interaction (HEI) is how humans affect and are affected by the surroundings. From the kinematic and kinetic points of view, the motion interaction between the surrounding and the human body can be called physical human-environment interaction (pHEI). Studying pHEI is very useful in understanding human-centered activities in daily live. The objective of this dissertation is to study the tracking of pHEI in daily applications via wearable inertial and contact sensor systems. In body motion tracking, multiple wearable inertial sensors are used to capture the human body kinematics. Meanwhile, contact sensors worn on the body are used to detect the contact interactions with the environment. To determine the precise human kinematic model of a human subject, a quick template-based calibration method is proposed. Subsequently, a three dimensional human motion tracking and localization method termed as *simultaneous localization and capture* (SLAC) based on the continuous contacts with the environment and the human body kinematics is introduced to record human motions and positions. For tracking of human motions with phases where there is no contact with the environment such as jumping and running, the *velocity based SLAC* (V-SLAC) and *acceleration based SLAC* (A-SLAC) are introduced. The proposed SLAC, V-SLAC and A-SLAC methods are able to simultaneously record body motion and track body location over a large space regardless of whether it is indoor and outdoor, or having or not having contacts with the environment. With the proposed quick template-based calibration method, precise human kinematic model can be achieved without using additional external devices. Experimental results and benchmark study with the optical-based Motion Analysis® system showed that the proposed SLAC can control the localization errors within 1% to 2% of the total distance travelled. The velocity errors of the V-SLAC can be controlled within 2% of the moving velocity for daily activities such as walking, jumping and jogging. Experiments on human subjects confirmed that full-body motion and the contact interaction during the pHEI can be properly captured in real-time. With

the development of more advanced integrated MEMS inertial sensing technology, SLAC, V-SLAC and A-SLAC can offer great advantage in many daily applications requiring human motion tracking and localization.

Chapter 1 Introduction

“The environment is everything that is not me”, said Albert Einstein [1].

Human-environment interaction (HEI) is how humans affect and are affected by the surroundings. Broadly speaking, HEI can be defined as the interaction between humans and surrounding ecosystems. HEI covers many broad human-environment interactions, for example, ecological and environmental interaction issues such as city construction, air pollution and transportation. At a personal scale, in the daily living aspect of HEI, humans can manipulate and converse with physical objects in their surrounding environments via coordinated speech, gesture and writings[1].

From the kinematic and kinetic point of view, interaction between the human and the environment refers to the relative motion and contact forces between the surrounding and the human body. For example, while walking, the body motion, the position trajectory, the contact locations and the ground reactions forces are all key features defining the interaction between the human body and the environment. To be specific, the motion interaction between the surrounding and the human body mechanism can be defined as *physical human-environment interaction* (pHEI). The basic rationale for pHEI is that humans live inside and is an inseparable part of the environment. Understanding the contacts acting on the human as well as the spatial relationship of the human within the environment will enhance the study of physical motion and interaction of humans.

In pHEI, humans serve as the central part performing activities within the environment facilities and surrounding objects. Studying the physical human-environment interaction is very important for almost all the human-centered activities in daily living. Firstly, when humans act in an environment, the whereabouts of them are usually very important for navigation and security purposes. For example, in an urban environment, people needs localization systems

to figure out their location and the way they want to go. First responders need to know the locations of themselves and their partners in order to collaborate with each other and conduct emergency rescues when necessary. Besides the location of the person, the motion interaction with the environment can also provide valuable information. In fitness trainings, motion studies, rehabilitations, entertainments, and sports competitions etc., the motions of human body and the relative spatial motion with respect to the surroundings are the key information pertinent to the human activities. Tracking the spatial motion interaction in such scenarios can benefit people in improving their performing skills (for sports and motion studies) and let other people know their conditions in their activities. For example, doctors care about the limb movements of patients for rehabilitation purposes. Coaches need the key parameters of the athletes to provide useful training instructions. In motion studies, taking yoga learning as an example, a yoga master needs to judge the correctness of the yoga postures of a student. Since human eyes cannot judge precisely on very detailed human motions, the tracking systems that can precisely measure the key parameters such as the position of the person, the body joint angles and the moving velocity etc., can be very helpful in such applications. In addition, human interaction with the environment is also very critical apart from the body motion of human. When people carry out their activities in the environments, their bodies contact with the environments. The contact provides the forces to support the human body, to accelerate or to decelerate the human body during motions. The contact forces also provide friction forces to prevent human limbs from slipping. For example, in dancing, the contact forces between the dancer's feet and the ground provides the forces to balance and to generate complex body motions. In the case of using hand-held tools (or gears), the contact forces also exist between the tools (gears) and the environments. These contact forces are very important for humans firstly to prevent them from injury and secondly to better fulfill the requirement of the activities. For example, in playing golf, the contact force between the golf club and the golf ball is an important parameter in determining the trajectory of the ball. It is also important to prevent

injuries to the arms in case the club hits the ground. The contact interactions are closely related to the kinetics of the human body. Tracking on the kinetic parameters during human-environment motion interactions are thus very important.

During the past two decades, many technologies on human motion tracking have been developed such as magnetic [2, 3], video cameras [4, 5], exoskeleton [6], ultrasonic [7], and inertial based systems [8-10]. Details of the literature review on motion capture systems can be found in [7-9]. Force sensors and force platforms [11, 12] have been developed to detect contact interaction and contact forces during human motions.

Although many devices have been developed for human motion and interaction tracking, many research problems still remain unresolved in the tracking of pHEI during daily activities.

In sports like dancing, playing badminton and practicing Kendo, humans act with contact interactions and different walking gaits while they carry out other body movements in the environment. These activities mostly take place in open and uncontrolled areas. Most laboratory-based tracking systems have a fixed set-up and limited capture volume. Therefore, it is usually impractical and not economical to use laboratory-based systems for motion and interaction tracking in such applications.

In monitoring the activities of patients and elderlies in a house or a hospital, the set-up of laboratory-based systems is also not practical due to economical concern and technical problem such as obstruction and capture volume limitations. A self-contained wearable tracking system would be more suitable and convenient to use. Similar conditions also apply to the tracking and analysis of workers' activities inside workspaces. In such activity monitoring applications, the system is expected to be able to provide real-time tracking data allowing the observers to obtain

immediate useful motion and interaction information in whatever conditions open or cluttered environments.

Wearable motion tracking systems have been introduced by researchers during the past decade. However, problems like *accurate localization of the human subject purely based on the wearable sensors*, and *the motion tracking over large areas* are still not properly solved.

To properly track a person's spatial position, body movements and the interaction with the environment, a precise kinematic model is needed for each human subject. There are anthropometry devices which can measure the dimensions of the human limbs in order to define the kinematic model. However, for daily use, it would be great if such devices can be avoided in order to save on money, preparation time and space in the room. Therefore, the following question arises: *Is there a calibration method of the human kinematic model that is time-saving and does not need external devices?* If yes, it would very useful for the wearable tracking system in daily use.

In sports training or exercises such as walking and jogging, the human subject acts in a large and open environment. The subject's body motion, position trajectory and moving speed are crucial parameters for performance evaluation. For jumping, jogging and running, which is different from walking in a manner that there are instances without contact between the foot and the ground, localization of the human body in such motions solely based on wearable sensors is still a challenge problem. Although additional infra-structure localization devices such as ultrasonic, Radio Frequency Identification (RFID) and Ultra-wideband (UWB) etc. can be installed in the surroundings for localization, in these sports and exercises related applications which take place in large areas, they are not economically viable. The GPS system is not precise enough for positioning accuracy below one meter and it is normally only available in open outdoor environments. Therefore, in these applications, the wearable system is expected to be able to accurately localize

the person, capture his body motion and interaction, and monitor his moving speed without depending on external infra-structures. However, for the existing wearable tracking systems, there are a number of technical gaps to fulfill these tracking requirements. Accurate velocity tracking of human subjects using wearable tracking system is still not properly solved. Localization and tracking of human subjects during such motions with non-contact phases using the wearable system is also not well- addressed. In many daily professional and casual activities such as polishing work pieces and playing tennis, the human body moves and interacts with the environment with hand-held tools (or gears). Movements and interactions of hand-held machine tools or hand-held sports gears are also important to understand. Integrated full-body motion and contact interaction tracking are a new topic in understanding how human actually work and play in the surrounding world.

Thus, in order to cope with these issues in the human-environment interaction, we embark on the study of tracking physical human-environment interaction via wearable sensors. The tracking methods include kinematic and kinetic information that lead to localization, body motion and interaction recording etc.

1.1 Research Issues in pHEI

Figure 1-1: Illustration of pHEI

Figure 1-1 illustrates the scenario of pHEI tracking via a wearable sensor system to bridge the gap mentioned in pHEI. The research issues in this dissertation are mainly focusing on solving the following problem when the human moves and interacts with the surroundings: *to study on the tracking methodologies based on a precise human kinematic model of the subject, and the corresponding appropriate wearable sensor system to accurately track the human motion and interaction with the environment.*

First of all, to accurately represent human motion, the human kinematic and kinetic models for the subject need to be clearly defined. The dimensions of the human skeleton model differ from person to person. Therefore, a calibration method that can quickly determine the body dimensions of every subject is needed. The

kinematics and kinetic model of the human subject is also needed in order to describe the human motion.

Second, it is also necessary to choose appropriate wearable sensor systems to meet the tracking requirements. Methods to define the relationship between the human body and the body sensors are needed so that the sensor measurements can be used to calculate the body motion.

During the interaction, the wearable motion sensor can measure body movements. The wearable force sensors can detect the contact events with the environment. In order to track the three-dimensional location of the human subject during interactions, research on how to combine the contact interactions and the body kinematics for localization and tracking of the human subject is necessary.

Moreover, in motions having instances without ground contact such as jumping, jogging and running, localizing human subjects in such instances is very challenging because it requires the estimation of more kinematic parameters such as body velocity and acceleration of the human in advance to have precise positioning results.

Finally, during full-body interaction with the surroundings, integrated full-body motion and interaction tracking need to be studied in order to have a more clearly understand the pHEIs.

1.2 Scenarios of pHEI Tracking

This dissertation investigates on such pHEI tracking via a wearable sensor system. As a main part of the work, the localization methods of human during different motion patterns and different contact interactions are studied in order to come up with systems and methods that are not only suitable for stable motions but also for dynamic motions like jumping and running.

Tracking the physical human-environment interaction via wearable sensors closely relies on the human body kinematics and kinetics, and the contact interactions with the environment. For example, when a human subject is climbing a ladder as shown in Figure 1-2, the human uses hands to hold on the ladder and uses the feet to stand on the steps. The motion of the body is determined based on the body kinematics and kinetics. Suppose the person moves from the posture in violet color to the posture in back color with both body movement and changes in contact interactions with the ladder. The hands holding the ladder and the feet standing on the steps represent the contacts between the ladder and the human. From the kinematic point of view, the human body can have internal motions without breaking the contact interactions due to the redundant degree of freedom in human body mechanism. These contact interactions in the environment become the *kinematic constraints* imposed on the human body motion.

Figure 1-2: Climbing a ladder

Tracking issues in pHEI

Firstly, in order to make the motion and interaction tracking of the human subject possible, the kinematics and kinetic model of the human body and the sensor systems are needed. Therefore, a system calibration is required to figure out the human kinematic model of the subject and the sensor positions with respect to the body limbs.

Secondly, based on the system motion tracking methodology using the wearable sensors, the body posture of the subject is captured and presented using the calibrated human kinematic model as shown in Figure 1-3 (a).

As illustrated in Figure 1-3 (b), at the same time, the contacts between the body and the ladder are recorded based on the contact sensors on the hands and the feet. The kinematic constraints on the human body come from the fact that the human cannot break the contacts with the ladder at the touch points when climbing. Therefore, the contact interactions will contribute in the localization of the human subject provided the contact positions are pre-determined.

To present the actual location of the person during the motion, a reference root point (p_0) on the human body is needed. After tracking the body posture and the absolute position of the contact points with respect to the environment (see point 1,2,3 and 4 in Figure 1-3 (c)), the location of the root point can be determined based on a localization method.

Because of inaccuracies in the human model and the sensor measurements, the captured posture of the human body may not satisfy the kinematic constraints from the contacts as shown in Figure 1-3 (c). Therefore, the posture fine tuning process is needed to “re-adjust” the body posture and correctly represent the contact interactions as illustrated in Figure 1-3 (d) (with correct contact constraints). Then, the motion and interaction with the environment is correctly tracked.

Figure 1-3. (a): Climbing a ladder—Body posture captured by motion sensors. (b): Climbing a ladder—Contact interaction detected from contact sensors. (c): Climbing a ladder—Localization. (d): Climbing a ladder—Posture fine tuning.

1.2.1 Interaction Tracking and Localization

The abovementioned tracking example of ladder climbing is a multi-contact problem with continuous contact interactions. In normal activities, the contacts occur between the human feet and the ground. In motions like walking and dancing, the contacts continuously exist between the human feet and the environment. In motions like jumping and running, there are instances that both feet are off the ground without contacting the environment which is called a *non-contact phase*. Localization of motion with non-contact phases is more difficult than motions with continuous contacts because there is no reference to localize the human subject during the non-contact phase. Here we mainly categorize the human motion with the lower limb motion interactions. Based on the contact interaction and the motion pattern of the lower limbs, the activity can be characterized into the walking, jogging, running and jumping.

Walking

In walking, the right and the left foot contacts with the ground alternatively, and each foot has a *stance phase* and a *swing phase* in one step cycle. Between the two *single foot support phases* when only one foot is in stance phase, there is a short double-foot support phase when both feet are in stance phase as shown in Figure 1-4 [13]. The average normal walking speed for a healthy adult is around 5km/h [14].

Figure 1-4: Walking phases

Figure 1-5: Running phases

Running

Running is a cyclic motion in which the feet contact and leave the ground in sequence. The running gait cycle has two major phases, *the support phase* followed by *the swing phase*. [15]. In running as shown in Figure 1-5, the right and the left foot support phase also occurs alternatively. However, they are different from walking in the way that in between the two single support phases, there is a *double-float phase* when both feet are off the ground[15].

Jogging

The definition of jogging as compared with running is mainly the speed. According to reference [16], the definition describes jogging as running at the speed slower than 10 km/h. Jogging is also distinguished from running by having a wider lateral spacing of foot strikes, creating side-to-side movement that likely adds stability at slower speeds or when coordination is lacking. The phases for running and jogging are the same. Therefore, this dissertation does not separate this two for localization study.

Jumping

Jumping is more complicated because there are many types of jumping. One way to classify jumping is by the manner of foot transfer [17, 18]. In this classification system, five basic jump forms are distinguished:

Figure 1-6: Jumping phases

Jump— jumping from and landing on two feet.

Hop— jumping from one foot and landing on the same foot.

Leap— jumping from one foot and landing on the other foot.

Assemble— jumping from one foot and landing on two feet.

Sissonne— jumping from two feet and landing on one foot.

Leaping gaits, which are distinct from running, include cantering, galloping, and pronging [19] .

Here we only discuss on the normal jump, jumping from and landing on two feet as shown in Figure 1-6. The jumping is divided into the following four phases, *approaching*, *take-off*, *flight* and *landing* [17, 18].

As the contact interaction and moving speed varies, different localization algorithms are needed to cater for motions with stable contacts and the motions with non-contact phases. In this dissertation, three localization methods catering for different contact conditions are introduced and studied.

1.2.2 Localization and Tracking Methods

1.2.2.1 SLAC: Simultaneous Localization and Capture

For walking localization, it is known that walking gaits require human feet in contact with the ground. Thus, by identifying the contact state of the human feet on

the ground and tracking the lower limb kinematics continuously at the same time, the 3D trajectory of the root point on the human body can be obtained over time through a proper human kinematic model.

The idea is illustrated in Figure 1-7. In the Initial phase for system initialization (1), the system registers the global position of the root point when $t=0$, $p_o(0)$, on the human body from the global coordinate, and the system calibration is conducted. When the subject starts to move, the sensors capture the lower limb postures. The trajectory of the root point can be computed with the human kinematic model. As the human continues to walk, the foot contact patterns are captured and the contact phases are identified based on the foot sensors measurements. Subsequently in Phase 4, the data tracking procedure repeats in the human walking motion. The walking patterns can be captured and handled in real time. The trajectory of the human subject $[p_o(0), p_o(t_1), p_o(t_2), \dots, p_o(t_n)]$ can be obtained. Interpolation of discrete root points sampled at a high sampling rate is applied to obtain a continuous trajectory.

Figure 1-7: Working principle of the SLAC method

This tracking method for continuous contact motions is termed as *Simultaneous Localization and Capture* (SLAC). In the mobile robot research on simultaneous localization and mapping (SLAM), the location of the robot and the traveling maps are generated. In the proposed SLAC method, the location and the body motion are captured. SLAC only relies on the body kinematic model and the contact interactions for localization and tracking.

1.2.2.2 V-SLAC

SLAC method relies on the foot contacts with the ground for computing the root position. When the non-contact phases come in during motions like the jumping and running, SLAC does not work anymore because the contact to the ground is no longer available. However, if the velocity of the root point $\mathbf{v}_o(t)$ can be accurately tracked, the location of the root point can be updated based on integrating the root point velocity over time during the non-contact phases.

Figure 1-8: Working principle of V-SLAC

The idea of a velocity based SLAC method (V-SLAC) is illustrated in Figure 1-8. Phase (1) is initialization. Phase (2) captures the motion and location, and at the same time track the root point velocity based on the velocity kinematics of the human body. In phase (3), the non-contact phase, the system computes the velocity based on the integration of the root point acceleration. The integration of the root point velocity can be applied to update the root position. In phase (4), contacts show up again, the root point velocity can be updated based on the human kinematic model. The tracking procedures repeat again. In this way, velocity tracking makes the localization during non-contact phase possible.

1.2.2.3 A-SLAC

In many application scenarios, people only concern about the trajectory and the moving speed of the subject. For example, in personal localization and jogging, the location and the velocity are the key interested parameters. In this case, it would be good if the system can have as few sensors as possible.

In V-SLAC, the velocity of the root point is tracked every time the right or the left foot contacts the ground. Therefore, wearable sensors on both legs are needed to track the kinematic parameters for the root velocity calculation. The velocity tracking during the non-contact phase comes from the integration of the root acceleration over time. Because of the root acceleration errors in the sensor measurement, the integration update on the velocity tracking will drift gradually over time. Therefore, the reference velocity from the lower limb kinematics should show up frequently for every step in order to prevent large drifting errors in the velocity.

If the error of the root acceleration can be estimated and eliminated, the integrated root velocity result can be more reliable in a longer period so that we can track only one leg's kinematics for the velocity update. In this case, the number of sensors for

the tracking system will reduce as sensors will be needed only on one leg instead of both legs.

The SLAC method with acceleration correction based on sensors worn on one leg is called A-SLAC as illustrated in Figure 1-9. The sensors are worn on the right leg in Figure 1-9. Phase (1) is initialization. In phase (2), *the right foot support phase*, the right foot stands on the floor. The velocity and location of the subject is tracked based on V-SLAC method. It is known that the acceleration error is the drifting rate of the integrated velocity. Therefore, the acceleration error is estimated based on an acceleration fine tuning algorithm by calculating the drifting rate of the integrated velocity. In phase (3), the right foot does not touch the ground (no matter whether the left foot contacts with the ground or not), the system tracks the velocity based on the integration of the fine-tuned acceleration. The location is updated based on the integration of this velocity. In phase (4), the right foot support show up again, the velocity can be updated based on the right leg kinematic model.

Based on SLAC, V-SLAC and A-SLAC, the human-environment motion and interaction can be fully captured via the wearable sensors.

Figure 1-9: Working principle of A-SLAC

In the full representation of the physical human-environment interaction, both the kinematic and kinetic tracking issues are investigated. With the tracking of human full-body kinematics, kinetic parameters such as the contact forces and the body joint forces can be measured and calculated using a proper human kinetic model. For example, in climbing the ladder, contact reaction forces from the ladders and efforts exerted on the body joints are the parameters of concern during kinetic tracking. This dissertation mainly focuses on the kinematic tracking issues. Implementations of the kinetic tracking system will be conducted in the future.

1.3 Objective and Scope

In this work, we aim to develop a wearable sensor based pHEI tracking system and corresponding methods that can accurately track human body motion, spatial location trajectory as well as the motion interaction with the environment. The system should be applicable to daily practical applications not only with stable motions like walking and climbing but also motions like jumping and jogging. The system should precisely record the body movement and the three dimensional position. Also, the velocity of the human subject needs to be tracked to represent his moving speed during the pHEI. The system should have the following characteristics:

- In order to present the human position correctly, localization error should be less than a foot length of the subject while moving in daily area. Therefore, the localization error should be within about 0.2m after traveling ten meters;
- The system should be able to track the velocity of the subject in order to present the speed of the motion. The velocity error should be at least within 0.1m/s in order to have practical value;

- The system should be able to correctly track the correct postures. Therefore, the orientation errors for the body segments should be at least less than 5 degrees;
- The system should be able to track the full-body motion and interaction, with correct contact interaction between the human body and the environment.

1.4 Organization of This Dissertation

Chapter 2 provides the literature review on human-environment motion interaction tracking. The tracking applications on the pHEI in the form of kinematics and kinetics are reviewed. Chapter 3 introduces the simplified human kinematic and kinetic model for human motion representation. The human kinematic model and the sensor kinematic model as well as the kinematic formulations are introduced. This provides the basis for the motion and interaction tracking in the following chapters. In Chapter 4, a self-contained quick calibration method to calibrate the human kinematic model and the system is introduced. Based on the calibrated model with precise body segment dimensions, the human body kinematics is fully defined. After introducing the kinematic/ kinetic model and the system calibration, the simultaneous localization and capture method SLAC for tracking motions with continuous contact interactions is introduced in Chapter 5. The experimental study of SLAC is presented to validate the system and method. Chapter 6 introduces the velocity tracking and localization method V-SLAC for tracking motions with non-contact phases such as jumping and jogging. The experimental study of the tracking experiment using V-SLAC is presented. Subsequently, an acceleration based localization method A-SLAC using three IMU sensors is presented. Chapter 7 discusses the full-body integration of the pHEI tracking system for daily practical applications. The tracking of full-body motion for kendo practice is chosen for demonstrating pHEI tracking. The evaluation of the pHEI tracking system is

discussed. Finally, Chapter 8 concludes the dissertation and describes the future work.

Chapter 2 Literature Review

The physical human-environment interaction pHEI covers a number of aspects. Detecting the whereabouts of a human subject with respect to the environment is very important for people to track the person. Second, the body motion of the human subjects and the contacts with the environment indicate how the human body moves and interacts with the surrounding. These are very important information for people to understand the human activities during the pHEI. Also, the contact forces between the human body and the environment and the reaction forces on the body are useful in sports and biometric applications. These lead to the kinetic tracking issues during the pHEI.

To make it clear in this review, tracking of spatial location of a human subject during the pHEI is termed as *personal localization*. Tracking of human body motion and motion interaction with the environments is termed as *motion and interaction tracking*. Tracking of kinetic parameters such as the contact and external forces is termed as *kinetic tracking*.

2.1 Personal Localization

Tracking the absolute position of a human subject in the environment is also known as personal localization/ navigation or human localization. Localization of human has been studied for decades by many researchers in applications such as emergency rescue [20-22], sports, [23, 24] and personal navigation [25-28] using different technologies. A complete review of the personal localization technology can be found in [29, 30].

In the pHEI, the personal localization system needs to determine the actual position of human with respect to the environment. For example, the localization system should be able to indicate the whereabouts of the person such as in which room, on

which floor, or more specifically the exact location of the human in the living room.

For personal localization, there are two main requirements for the tracking technologies. One is that the localization should be accurate enough for the applications. The other is that the system installation should be economical and convenient to use. Although absolute external positioning devices such as ultrasound [20], Laser [31], camera [28], and RFID can track the location of a person, this needs additional installation of infra-structures with high expenses. Also, these devices are only available within some fixed area with limited volume, not available for daily practical applications. GPS is a convenient localization system for outdoor applications. But in the indoor environments, the signal is not commonly available [29, 32-35].

The properties of existing human localization technologies are compared in Table 2.1.

Table 2.1: Comparison of existing human localization technologies

Technology	Technology in details	Localization methods				Position Accuracy	Orientation	Volume	Update rates	Indoor/ Outdoor
		TR	PR	SA	DR					
RF	GPS,GNSS	√		√		10~20 meters	Yes	Unlimited	Slow	Outdoor
	Local area networks	√	√	√		several meters	Yes	Large	Slow	Outdoor
	RFID		√	√		several meters	No	Limited	Slow	Indoor
Ultrasonic		√				several centimeters	Yes	Limited	Slow	Indoor
Image				√		submeter level	Yes	Limited	Slow	Indoor/ Outdoor
Inertial					√	Submeter level	Yes, <1°	Unlimited	Fast	Indoor/ Outdoor
RFID: Radio Frequency Identification; GNSS: Global Navigation Satellite System * TR=Triangulation, PR= Proximity, SA=Scene analysis, DR=Dead reckoning

Figure 2-1: The boot localization system from MINT, DARPA

In daily human-environment motion interaction, a self-contained system and localization method is useful and convenient. During the past decade, IMU sensors are applied for personal localization based on the Personal Dead Reckoning (PDR) algorithm where the absolute location of the subject is calculated based on the accumulation of stride lengths [36]. The Zero-Velocity Updates (ZUPTs) method proposed by Foxlin [26] can provide localization results with errors within 1% of the total distance. The shoe-mounted inertial sensors are used to track the location of the soldiers or first responders [25, 26]. Figure 2-1 shows the inertial sensitive shoes for navigation of soldiers from the MINT project, DAPPA [27].

This inertial navigation with shoe-mounted IMUs using ZUPTs method can provides good estimation of the subject locations. As this method is dependent on the *stance phase* of the foot to correct the sensor measurement errors, if time duration of a swing phase is more than a few seconds, the position estimation would be largely unreliable [26].

Another inertial based personal dead reckoning method roughly estimates the walking speed and distance based on the pattern of walking accelerations [28]. This method is 2D localization with moderate accuracy, and it is also quite user

dependent. Woodman proposes a 2.5D indoor user location tracking method based on environmental layouts [35]. This method needs the pre-defined maps of the environment. As existing shoe-mounted tracking devices only have coarse location information, it is insufficient to fully understand the posture behavior of a subject most of the time.

The recent Inertial SLAM (simultaneous localization and mapping) technology [37-39] based on camera and an inertial sensor is capable of tracking the spatial motion of object, which is proper for automobile and aircraft localization. For human spatial localization and capture, the extra cameras will increase the cost and the complexity of the whole system and make the computation too complex for real time human motion tracking. Another critical issue is that when occlusion happens, the camera cannot work. Because of the same reason, other camera based localization techniques (computer vision [28] and Visual SLAM [39-41]) are also not applied in this dissertation.

In daily practical applications, it would be useful to have a method to accurately track the 3D location of the human subject as well as tracking the body motion of him based on the wearable sensors without extra devices for localization.

2.2 Motion and Interaction Tracking

In the description of motion and interaction, the body movement, the spatial location and the contact interactions are the key parameters. Based on the tracking parameters for applications in motion and interaction tracking, the tracking problem can be divided into three categories.

(1) *Body movement tracking*: if only the human body movement is of interest in the tracking applications.

(2) *Spatial Motion tracking*: if the spatial human motion with respect to the environment is of interest (body movement and spatial location).

(3) *Motion and interaction tracking*: if the spatial human motion and the contact interacts are of interest.

Body movement tracking

For body movement tracking in many scenarios, only the motions of the body joints are of interest. For example, for the study of the biomechanics, the joint movements are usually of interest. During the past two decades, many research work on using the wearable sensors to track the human body joint motions have been conducted on the trunk [42], the ankle , the knee [43, 44], upper arm joints [45-47] etc.

In case of interaction with the virtual environment or with remote control, for example, playing games with body sensors and robot tele-operation, joint motions are tracked and retargeted to the virtual characters or the robot to realize the desired tasks. A tele-operated NASA Robonaut uses the IMU sensors to track the operator's upper arm motion which is retargeted to control a robot arm, as shown in Figure 2-2.

Figure 2-2: Motion capture from inertial sensing for humanoid tele-operation [48]

Figure 2-3: Motion capture system for everyday practice, MIT [7]

Apart from the tracking of individual body joint, the full body movement tracking are also studied. Daniel et al. in MIT built a motion tracking system for everyday practical activities using inertial sensors and ultrasonic sensors [7] (see Figure 2-3). Movements for daily activities such as driving, riding bicycle, playing Ping-Pang and skating have been captured by this system. MetaMotion introduces the inertial MoCap Gypsy® using eighteen IMUs [6] and the exo-skeleton based Gypsy 7™ (in Figure 2-4), which can be used for body movement tracking applications in various types of pHEIs.

These systems either do not have the localization function or use external positioning devices to measure the position of the subjects.

Figure 2-4: Gypsy motion tracking systems [6]

Spatial Motion tracking

In the spatial motion tracking of the human, the spatial location trajectory of the subject is of interest. This is actually the combination of the human localization as well as the body movement tracking. For many applications such as animation, entertainment and film making where the activity of human in space are needed, spatial motion tracking can provide useful motion data.

In film making and video gaming applications, the motion tracking technology is extensively used to track the actual human motion. The human motion data is used to generate the vivid human-like motions in the applications [9]. In the recent films with computer-generated creatures like the “The Lord of the Rings” (Figure 2-5) [9], “Avatar (Figure 2-6)” [34] and “King Kong”, motion tracking technology is applied in the film generation. The actor/actress performs in the required scenes in the film during which their motions are captured based on the motion capture system. The captured motion of the actors/ actresses can be streamed and fitted into the computer-generated creatures for the film generation [9].

Figure 2-5: Motion capture technology in movie “The Lord of the Rings” [9]

Figure 2-6: Motion capture technology in movie “Avatar” [48]

Figure 2-7: Motion tracking technology in FIFA [36]

Video games also use motion capture to animate the characters in the games. In the soccer game FIFA, the motion of the athletes are tracked in a controlled environment. These motion features are used to generate the vivid behavior of the corresponding virtual players (Figure 2-7) [34]. This kind of technology makes the *role play games* more intuitive and enjoyable.

In these application scenarios, the actors or the athletes need to perform in the required scenes, and the spatial motion is defined based on the scenes. Therefore, accurate tracking of the spatial motion of human subjects during pHEI is very useful.

Figure 2-8: Xsens full-body motion capture suit

For the spatial motion tracking of the subject, the optical motion tracking system is frequently used. There are also wearable solutions. The Xsens company developed the commercial IMU full-body MoCap “MVN”, “MVN Biomech” and “MVN Biomech Awinda™” as shown in Figure 2-8. The company uses the inertial navigation technology to solve the localization problem [6]. Double integration of the body segment accelerations and limb length constraints are combined to estimate the absolute position of the subject [49-51]. Based on [52], the localization accuracy is moderate. They have not report the scientific localization results during motions with flying phases like jumping and jogging in their publications.

Besides spatial motion tracking, in many cases it is also quite important to track the interactions between the human and the environment.

Motion and interaction tracking

In motion and interaction tracking, the spatial motion of the human subjects and the contacts with the environment are required. The contacts define the relative position between the human body segments and the surrounding structures when the person acts in the environment.

Fujimori et. al. from University of Tokyo developed a motion capture system with tactile sensors. Using the tactile sensors to track the contact conditions on the body, the system is able to correctly track the spatial motion and interaction with the environment structures. As shown in the second row of Figure 2-9, the system with tactile sensing can correctly track the actual motion and interaction without awkward result as shown in the third row where the contact information is not tracked. The method was only demonstrated on the static postures rather than continuous motions.

Figure 2-9: Motion tracking with motion tracking suit and tactile sensors. Top: actual motion. Mid: motion with tactile correction. Bottom: motion without tactile correction [53]

Sports tracking are typical examples of motion and interaction tracking. Matthew (Massey University, Wellington, New Zealand) developed a Fusion Capture System applied to the optimization of athlete performance in ski racing [24] (see Figure 2-10). The subject's ski motion with respect to the actual field and the gates in the environment are tracked based on combining the sensing data from camera, GPS, and inertial motion sensors.

In the human interaction with the virtual environment such as the on-line motion learning [54], the robot tele-operation [48] and controlling the characters in a virtual environment [54-56], the virtual characters are controlled through tracking the human subject's actual motion and retargeting the motion onto the virtual characters in the simulated environment. In this case, the interaction happens between the virtual character and the simulated environment, but still controlled by the real human motion.

Figure 2-10: Fusion motion capture for optimization in alpine ski racing [24]

It is mentioned in [57] “Interactive control of virtual characters through full-body movement requires accurately reproducing a performer’s motion while accounting for surrounding obstacles”. It means that it is necessary to be aware of the surrounding objects in the environment while fully presenting the precise body motion in order to avoid the physical contact or visual sink-in problems. As illustrated in Figure 2-11, when a person uses the capture system to control an avatar to get a bottle inside the environment, the arm should not “sink-in” to the tables while fetching it [57].

Figure 2-11: The motion and interaction while fetching a bottle around the structures.

Figure 2-12: Controlling the avatar by performing in front of cameras [56].

Similar scenarios also applies to the real-time control of avatars in three-dimensional computer games with human characters [56]. In Figure 2-12, the human is controlling the avatar in the game by performing the motion in the same environment structures in front of a camera.

If the virtual avatar is replaced with a robot, the human motion will control the robot to interact with the environment, as illustrated in Figure 2-13.

In these applications, the contacts between the human body and the environment need to be identified in order to correctly represent the motion interaction. The full tracking of motion and interaction require the precise kinematic modeling, motion tracking, contact detection and localization of the subject.

Figure 2-13: ExoHand – human-machine interaction [58]

2.3 Kinetic Tracking

Kinematic tracking mainly discusses the relative motion and the interaction with the environment. The force interaction is also an important part of pHEI, especially when people are interested in the reaction forces during the human activities.

In sports training and working, the human interacts with the environment and the operating hand-held gear or working tools. The experimental contact forces are very usually very important quantities for these kinds of human activities. For example, for a worker polishing a fan blade surface, the contact forces between the contacting surface and the hand-held polishing machine affect the polishing speed and accuracy of the polishing surface. In sports, the contact force is also a useful parameter to evaluate the skills of the exercisers. More importantly, tracking the kinetics during the motion interaction can contribute in injury prevention if the tracking system can tell which kinds of motion or contact posture are more likely to have large reaction forces on the joints or the bones.

Figure 2-14: Spatial motion and ground reaction force interaction during the ski racing

In the previously mentioned ski tracking system [23, 24, 33], apart from the spatial body motion, the ground reaction force between the athlete's skis and the snow surface during the ski racing is also recorded (the magnitude of the force is illustrated by the bars under the feet in Figure 2-14). The author state that round reaction forces are very important in ski racing because they are directly related to the athlete's performing techniques.

In biomechanical research, gaits study is a typical example of the kinetic pHEI which is closely related to the spatial motion of the human subjects and the ground reaction forces. The profile of the ground reaction force is used for diagnosis and gait analysis purposes. The abnormal pattern of the ground reaction force while walking is useful for the doctors to diagnose the abnormal gaits of patients. Motion tracking system with contact force platforms, or more specifically, gait laboratory (Figure 2-17) has been applied to the gait analysis for decades [11]. In a full representation of the gait analysis, there are also kinetic issues such as measuring the joint reaction forces and estimating the muscle strengths, as illustrated in Figures 2-15 and 2-16.

Figure 2-15: Biomechanics motion capture VICON [59]

Figure 2-16: Using the EMG and optical system to study muscle and joint function in human locomotion [60]

Nakamura et. al. in University of Tokyo worked on the muscle strengths estimation based on their muscle model of the human body using the optical motion capture system, the force platform and the EMG (Electromyography) sensors [61, 62], as illustrated in Figures 2-18 and 2-19. Based on the kinetics of the human body, the EMG measurements and the body muscle model, the strength of hundreds of muscles are estimated while the subjects take out various motions. The whole-body muscle activity can be visualized while the subject do motions in real time. The yellow muscles are activated muscles with high tension.

Figure 2-17: Layout of the gait laboratory with cameras and force platform [11]

Figure 2-18: System setup of the musculoskeletal-see-through system [62]

Figure 2-19: Musculoskeletal-see-through mirror: whole-body muscle activity visualization

Figure 2-20: Polishing the surface of a car body [63]

When humans interact with the environment with the hand-held gears or machine tools, the contact interaction occurs between the human and the hand-held device, and also between the hand-held device and the environment. Figure 2-20 illustrates a case when a worker is polishing the surface of a car door [63] using the polishing tool. The postures of the workman and the contact forces between the polishing wheel and the contact surface of the environments are critical in maintaining the polishing quality. Similar condition also applies to sports with hand-held gears such as playing tennis, golf and, kendo etc. In these scenarios, the motion interactions occur in an open space. It is possible to capture the human motion and the contact forces during such exercises using wearable devices. However, such tracking applications with force interactions are not much addressed in current literatures.

2.4 Summary

This chapter reviews the related works on the tracking of physical human-environment interaction. From the abovementioned wide range of applications, it is clearly shown that the study on tracking the physical human-environmental motion interactions is very important and useful in most of the human-centered activities.

Although there are many tracking devices proposed in the kinetic and kinematic tracking applications, the relatively mature technologies are basically restricted to industrial applications within controlled small volumes. In the tracking of pHEI for normal users' daily practical applications, there are still many research problems that remain unresolved. Therefore, a systematic study on the system design and optimization, the tracking methodologies need to be conducted.

Chapter 3 Simplified Kinematics and Kinetics of Human Body

Human body is a sophisticated biological structure consisting of joints of many different types and limbs with different dimensions. The human body also has a muscular skeleton structure which possesses compliance in the joints and motion limitations due to the property of muscle and the bones [64]. Because of the complexity of the biological structure, it is impractical to have a very accurate kinematic model of the human subject to describe the casual movement of a human and his interaction with other entities. In most of the practical applications, a simplified human model is sufficient to describe the motion information needed [65]. In a simplified human kinematic model, each limb segment can be considered as a rigid link connected to body joints which can be modeled as hinge joints, universal joints or spherical joints according to the degrees of freedom in the body joints. Such simplification significantly makes the human kinematic model implementable to devices with minimal computing resources.

In this chapter, the simplified human kinematic model is first introduced. The formulations of the kinematic model and the kinematic uncertainty are discussed. Then, the kinematics with the sensor system is discussed. The simplified kinetic model is introduced at the end.

3.1 Hierarchy of Human Annotation Structure

In mechanism design and analysis, a kinematic graph of the limbs and joints can illustrate the hierarchy of the complex kinematic chain [66]. In a kinematic graph, limbs and joints in the model are replaced by vertices and edges. In a simplified kinematic model, the human body segments and joints can also be considered as kinematic chains. Hence, it is possible to use a kinematic graph to represent a human body with body segments as vertices and body joints as edges. This graph

of the human body possesses a tree-like structure as shown in Figure 3-1. A kinematic tree starts with a root vertex. In the human kinematic graph, the root is chosen on the pelvis segment. The center of gravity (CG) of a human normally falls in the pelvis segment. The location of a root point on the pelvis can be defined to be the 3D position of the human. Through tracking the position of the root point, the trajectory of the human subject can be determined. The rest of the body segments (vertices in the tree-like structure) follow the standard human anatomy.

The directional edge represents the body joint motion between the adjacent body segments. This hierarchical arrangement of the body structure will facilitate the establishment of the body frames needed for body posture and motion representation.

3.2 Coordinate Frame Definition

Figure 3-1: Hierarchy of the human model

To describe the posture and the location of the human, coordinate systems of the human body and the global reference need to be established. Referring to the hierarchy graph in Figure 3-1, the body segments are represented by vertices and body joints are represented by edges.

First of all, a fixed global coordinate frame f_w is defined as the reference frame in the environment. In this dissertation, f_w is defined according to the *local navigational frame* of the IMU sensors used in the study, *with the X-axis points to the north, the Y-axis points to the east, and the Z-axis points downward*. The pelvis body frame is defined as the root coordinate frame whose origin is at the root point which is assigned at the center of two hip joints. The position and orientation of the human subject are thus represented by the root frame.

The postures of limbs are described by local coordinate frames rigidly fixed to the limbs, as shown in Figure 3-2. For convenience, in the initial standing posture as shown in Figure 3-2, (Note that this figure is a front view projection of the 3D human body model) all the body coordinate systems of the subject are chosen such that X-axis points to the ventral direction (front), the Z-axis points caudal direction (downward). The Y-axis is determined based on the right-hand rule. Therefore, all the body segment frames are in the same direction in the initial posture. In this way, the relative initial posture between adjacent body frames defines the skeleton dimensions used in the human model as listed in Table 3-1. As illustrated in Figure 3-2, the frame name and the location of frame origins are provided in Table 3-1.

The frames are defined following the hierarchy of the human skeleton model. The root frame is presented by frame 0. For the left side, the lower body frames are defined as follows. Left thigh frame: L1. Left shank frame: L2. Left foot frame: L3. Left upper arm: L4. Left forearm: L5. Left hand: L6.

For the right side: Right thigh frame: R1. Right shank frame: R2. Right foot frame: R3. Right upper arm: R4. Right forearm: R5. Right hand: R6. Upper body frame:

U1. Head frame, H1. The hierarchy structure provides the relationships between frames. A parent-child frame pair consists of two adjacent frames with the one closer to the root frame being the parent frame and the subsequent one being the child frame. The skeleton dimensions for each body segment are presented by a 3D vector in its body frame. This vector points from the origin of the parent frame to that of the child frame. The parameters for all body segments are shown in Table 3-1, and illustrated correspondingly in Figure 3-2.

Figure 3-2: Layout of body frames in the human kinematic model

Table 3-1: Parameters for body segments

Segments	Frame Name	Frame Origin	Parent	Child	Limb
Head	H1	Top of the neck	U1	N/A	r_{H1}
Trunk	U1	Mid of Shoulders	f0	R4,L4&H1	r_{TR} , r_{TL} & r_{TH}
Right Upper Arm	R4	Right Shoulder	U1	R5	r_{R4}
Right Forearm	R5	Right Elbow	R4	R6	r_{R5}
Right Hand	R6	Right Wrist	R5	N/A	r_{R6}
Left Upper Arm	L4	Left Shoulder	U1	L5	r_{L4}
Left Forearm	L5	Left Elbow	L4	L6	r_{L5}
Left Hand	L6	Left Wrist	L5	N/A	r_{L6}
Pelvis	f0	Root	Null	L1,R1&U1	r_{R0} , r_{L0} & r_{U0}
Right Thigh	R1	Right Hip	f0	R2	r_{R1}
Right Shank	R2	Right Knee	R1	R3	r_{R2}
Right Foot	R3	Right Ankle	R2	N/A	r_{R3}
Left Thigh	L1	Left Hip	f0	L2	r_{L1}
Left Shank	L2	Left Knee	L1	L3	r_{L2}
Left Foot	L3	Left Ankle	L2	N/A	r_{L3}

These dimension parameters as listed in the last column of Table 3-1 need to be calibrated properly in order to minimize the posture and the location errors in

motion tracking. The calibration of these body dimensions is discussed in the Chapter 4.

3.3 Formulation of the Simplified Kinematics

To describe the human motion, a human kinematic model with proper body sizes and joints needs to be defined following the hierarchy of the human body. In robotics, the Denavit–Hartenberg method is frequently used in kinematics formulation. However, when the link parameters are not precise, a calibration procedure is required all the time to determine the kinematic model. The D-H parameterization method becomes infeasible due to its minimal representation causing calibration singularity [67, 68]. In this dissertation, Product of Matrix Exponentials (POE) is introduced to represent the human kinematics. The POE method has uniform representation of the revolute and the prismatic joints and is free from calibration singularity of parallel revolute joint axes [69]. In the robot calibration literatures, there are two types of POE formulations: the global and the local POE methods. For the global frame representation of the POE formula, the twists of the joints are presented in the global frame. For the local frame representation of the POE formula, the twists of the joints are presented in their respective local frames. In this work, the local POE model is chosen due to the establishment of the local body segment frames and the subsequent orientation sensing technique. More detailed information about the POE can be found in [69, 74].

In order to make the notation easy to present in the forward kinematics of the human body, here we define the body segment frames in the following manner:

1. Each limb kinematic chain starts from the root frame and ends at one distal limb (the hands, the feet and the head).
2. For each limb kinematic chain, there is one unique chain ID to address it.

3. In each limb kinematic chain, the frame is labeled sequentially by 0, 1, 2, 3,....
The root frame is always the base which is itemized by (0).

The chain ID and the number of the limbs are defined below:

Limb Chain (C1): Root (0)→Right Thigh (1) →Right Shank (2) →Right Foot (3).

Limb Chain (C2): Root (0) →Left Thigh (1) → Left Shank (2) → Left Foot (3).

Limb Chain (C3): Root (0)→Trunk (1)→Right Upper Arm (2)→Right Forearm (3)→Right Hand (4).

Limb Chain (C4): Root (0)→Trunk (1)→Left Upper Arm (2)→Left Forearm (3)→Left Hand (4).

Limb Chain (C5): Root (0) →Trunk (1) → Head (2).

Figure 3-3: Local POE kinematics

In this manner, each kinematic chain will contain only one serial of frames: 0, 1, 2, 3..... The notion of the adjacent frames can be conveniently denoted by the subscript $i-1$ and i . This is necessary to simplify the subscript of the notations. To distinguish all the notations, we use the superscript to denote the chain number and subscript to denote the number of a limb in the chain. For example, ${}^c\mathbf{R}_l$ denotes the orientation of the right thigh. Note that *in the formulation of one kinematic chain, the superscript is omitted when there is no confusion with the limb chain.*

3.3.1 Local POE Formulation

Denote the body coordinate frame on the limb i by frame f_i . Let the frame f_{i-1} and f_i be adjacent and the corresponding limbs are connected by the joint i , as shown in Figure 3-3. Then the relative posture of frame i with respect to frame $i-1$ under a joint displacement q_i can be described by

$$\mathbf{T}_{i-1,i}(q_i) = \mathbf{T}_{i-1,i}(0)e^{\hat{\xi}_i q_i}, \quad (3-1)$$

where $\mathbf{T}_{i-1,i}(0)$ represents the initial pose of frame i in frame $i-1$. In the body kinematic model, the relative initial posture between frame i and frame $i-1$ is a pure translational matrix (because all initial posture of the body frames are defined to be parallel, as stated earlier in the section 3.2).

$$\mathbf{T}_{i-1,i}(0) = \begin{bmatrix} \mathbf{I}_{3 \times 3} & \mathbf{l}_{i-1,i} \\ 0 & 1 \end{bmatrix}, \quad (3-2)$$

where $\mathbf{l}_{i-1,i}$ ($\mathbf{l}_{i-1,i} \in \Re^{3 \times 1}$) is the initial position of origin of the frame f_i with respect to frame f_{i-1} , which can be determined by the calibration procedure. The joint motion, which represents the posture change of the frame f_i with respect to frame

f_{i-1} , can be described by a twist motion $e^{\hat{\xi}_i q_i}$ captured by the sensors. Here, $\hat{\xi}_i \in se(3)$ ($se(3), so(3), SE(3), SO(3)$ is defined in the list of symbols) is the twist associated with the joint i . It can be expressed in frame f_i as follows,

$$\hat{\xi}_i = \begin{bmatrix} \hat{\omega}_i & v_i \\ 0_{3 \times 3} & 1 \end{bmatrix}, \quad (3-3)$$

where $v_i = [v_{ix}, v_{iy}, v_{iz}]^T \in \mathbb{R}^{3 \times 1}$ and $\hat{\omega}_i \in so(3)$ is the skew-symmetric matrix of $\omega_i = [\omega_{ix}, \omega_{iy}, \omega_{iz}]^T \in \mathbb{R}^{3 \times 1}$, and

$$\hat{\omega}_i = \begin{bmatrix} 0 & -\omega_{iz} & \omega_{iy} \\ \omega_{iz} & 0 & -\omega_{ix} \\ -\omega_{iy} & \omega_{ix} & 0 \end{bmatrix}. \quad (3-4)$$

A complex body joint can have both rotational motion and translational motion. Therefore, the twist motion of the joint is a general 6-DOF displacement to be represented by an $SE(3)$ matrix as shown in the following equation,

$$e^{\hat{\xi}_i q_i} = \begin{bmatrix} e^{\hat{\omega}_i q_i} & v_i q_i \\ 0_{3 \times 3} & 1 \end{bmatrix}, \quad (3-5)$$

where $e^{\hat{\omega}_i q_i} = \mathbf{R}_{i-L,i}$ denotes the rotational motion and $v_i q_i = \delta p_i$ denotes the translational motion of the joint i . In this simplified human kinematic model, the slight translational motions in the body joints are not considered. In practical applications, it is reasonable to consider the body joints as rotational joints without translational motions. Thus, the following reasonable approximation is made:
 $v_i q_i = \delta p_i = 0$ "

Moreover, q_i is the displacement of the joint i and

$$e^{\hat{\omega}_i q_i} = \mathbf{I} + \hat{\omega}_i \sin q_i + \hat{\omega}_i^2 (1 - \cos q_i) \quad (3-6)$$

is the rotational matrix for rotating around the axis ω_i for an angle q_i .

3.3.2 Forward Kinematics for the Human body

The posture of the root frame represents the absolute location and orientation of the human subject in the environment. The origin of the root point is chosen at the middle point of the two hip joint centers. When describing the internal body posture, this root frame is chosen as the base frame (0). Then, the relative posture between the root frame and the distal limb such as feet, hands and head, is determined by the motions of the limb kinematic chain between them. In the local POE formulas of the kinematic chains, the initial relative posture of the body frames $T_{i-1,i}(0)$ and the joint twist motion $e^{\hat{\xi}_i q_i}$ are required. Based on hierarchy graph of the human body and the numbering of the limbs for the specific kinematic chain (from 0,1, ... to ,n), the posture of the end can be calculated from the forward kinematics of the kinematic chain as

$$\begin{aligned} T_{0n}(q_1, q_2, \dots, q_n) &= T_{0,1}(q_1) T_{1,2}(q_2) \cdots T_{n-1,n}(q_n) \\ &= T_{0,1}(0) e^{\hat{\xi}_1 q_1} T_{1,2}(0) e^{\hat{\xi}_2 q_2} \cdots T_{n-1,n}(0) e^{\hat{\xi}_n q_n} \end{aligned} \quad (3-7)$$

Substituting Equation (3-2) and Equation (3-5) into Equation (3-7), and note that,

$\prod_{i=1}^k R_{i-1,i} = R_{0,k}$, we obtain

$$T_{0n}(q_1, q_2, \dots, q_n) = \begin{bmatrix} R_{0,n} & p_{0n} \\ \mathbf{0}_{1 \times 3} & 1 \end{bmatrix}, \quad (3-8)$$

where

$$p_{0n} = \sum_{i=1}^n R_{0,i-1} (l_{i-1,i} + \delta p_i). \quad (3-9)$$

Let T_0 denote the displacement of the root with respect to the global reference frame

$$T_0 = \begin{bmatrix} \mathbf{R}_0 & \mathbf{p}_0 \\ \mathbf{0}_{1 \times 3} & 1 \end{bmatrix}. \quad (3-10)$$

Then, the posture of the end frame T_n with respect to the global frame is

$$T_n = T_0 T_{0n} = \begin{bmatrix} \mathbf{R}_n & \mathbf{p}_n \\ \mathbf{0}_{1 \times 3} & 1 \end{bmatrix}, \quad (3-11)$$

where

$$\mathbf{p}_n = \mathbf{p}_0 + \sum_{i=1}^n \mathbf{R}_{i-1} (\mathbf{l}_{i-1,i} + \delta \mathbf{p}_i). \quad (3-12)$$

In this manner, the relative displacement between the root frame and the distal frame is determined. Therefore, when the posture of the root frame is known, the spatial displacement of the distal limbs can be calculated based on Equation (3-12).

Besides location information, the velocity of the distal limb is also useful to present the motion speed. Differentiating the above Equation (3-12), we obtain the velocity of the distal limb

$$\begin{aligned} \mathbf{v}_n &= \mathbf{v}_0 + \sum_{i=1}^n \boldsymbol{\omega}_{i-1} \times (\mathbf{R}_{i-1} \mathbf{l}_{i-1,i}) \\ &= \mathbf{v}_0 + \sum_{i=1}^n \mathbf{R}_{i-1} (\boldsymbol{\omega}_{i-1} \times \mathbf{l}_{i-1,i}) \end{aligned}, \quad (3-13)$$

where the orientation and the angular velocity of limb i with respect to the global frame are denoted by $\mathbf{R}_i$ and $\boldsymbol{\omega}_i$ respectively. The angular velocity of limb i with

respect to its body frame is denoted by ω_{ib} . The velocity of the root point is denoted by v_θ .

Due to the slight dimension errors in the kinematic model and the sensor measurement errors, the kinematics between the root and the distal limb bound to have some uncertainties. The kinematic uncertainty is discussed in next section.

3.3.3 Uncertainty in Human Kinematics Model

After determining the dimensions of the limbs, a proper kinematic model to describe the human motion can be generated. Since the accuracy of the biometric data of the human is not as good as the rigid robotic system, the limb dimensions and orientations bound to have measurement errors. Given the model of uncertain parameters inside the kinematic model, the uncertainty of the estimated distal limb position can be calculated. This is crucial because such uncertainty would affect the accuracy of the body postures and also the correct presentation of the contacts with the environment as shown in section 5.3.

First, we assume that the skeleton dimensions are imprecise, and let $\delta l_{i-1,i}$ represent the slight dimension errors of the limb i . The initial posture between frame i and frame $i-1$ becomes:

$$T_{i-1,i}(0) = \begin{bmatrix} I_{3 \times 3} & l_{i-1,i} + \delta l_{i-1,i} \\ \mathbf{0}_{1 \times 3} & 1 \end{bmatrix}. \quad (3-14)$$

Second, we assume that the limb orientation is also imprecise. Let $\delta R_{\theta,i}$ represent the rotational error of joint i with respect to the base root frame.

Because of the complexity in the human kinematics, having an exact uncertainty model for the complex human body mechanism is almost impossible. In this dissertation, we do not analyze the exact property of the uncertainty parameters.

The properties of these parameters are assumed to be normally distributed with the standard deviations as shown in Table A-1 of Appendix A.

The position and velocity uncertainties of the distal limbs can be analyzed based on the uncertainty model discussed below.

3.3.4 Uncertainty in Position

Due to the kinematic uncertainty, the relative posture between the root and the distal limbs are also inaccurate. With the orientation error of limb i $\delta R_{0,i}$, and the link length error $\delta l_{i-1,i}$, and according to Equation (3-12), we have:

$$p'_{0n} = \sum_{i=1}^n R'_{0,i-1} (l_{i-1,i} + \delta l_{i-1,i}). \quad (3-15)$$

Note that $R'_{0,i} = \delta R_{0,i} R_{0,i} = e^{\delta \hat{\omega}_i} R_{0,i}$, $\delta R_{0,i}$ represents the orientation measurement errors and $\delta \hat{\omega}_i$ denotes the corresponding $se(3)$ skew-symmetric matrix as introduced in section 3.3.

Thus, the position error on this distal limb is

$$p'_{0n} - p_{0n} = \sum_{i=1}^n [(e^{\delta \hat{\omega}_{i-1}} - I) R_{0,i-1} l_{i-1,i} + R'_{0,i-1} \delta l_{i-1,i}]. \quad (3-16)$$

Note that when $\delta \omega_i$ is small, $(e^{\delta \hat{\omega}_i} - I) \approx \delta \hat{\omega}_i$, and $R'_{0,i-1} \approx R_{0,i-1}$. Thus, we have

$$\delta p_n = p'_{0n} - p_{0n} \approx \sum_{i=1}^n [-(R_{0,i-1} l_{i-1,i}) \times \delta \omega_i + R_{0,i-1} \delta l_{i-1,i}]. \quad (3-17)$$

Rearrange the above Equation (3-17), we have

$$\delta p_n = BX, \quad (3-18)$$

where

$$B = \text{diag}(-(R_{0,1} l_{1,2})^\wedge, -(R_{1,2} l_{2,3})^\wedge, \dots, -(R_{0,n-1} l_{n-1,n})^\wedge, I, R_{0,1}, \dots, R_{0,n-1}) \in \Re^{6n \times 6n},$$

and $X = [\delta\omega_1^T, \delta\omega_2^T, \dots, \delta\omega_n^T, \delta l_{0,1}^T, \delta l_{1,2}^T, \dots, \delta l_{(n-1),n}^T]^T \in \Re^{6n \times 1}$.

3.4 Kinematics with Sensors

In this dissertation, the IMU sensor is used as the orientation measurement sensor. Since these small-sized wearable trackers have little restriction on the human movement and can provide accurate motion capture results, these devices are suitable for applications in intuitive digital media, medical care, sports and entertainment in large areas and flexible environments [11, 23, 42, 43, 70, 71]. As the IMUs are decreasing in size and price, and increasing in accurate and reliability in measurement, these types of sensors have the potential widespread in the daily practical applications.

3.4.1 Principle of the IMU Sensors

The IMU sensor includes three-dimensional gyroscopes, accelerometers and the magnetometers (see Figure 3-4), which can estimate the kinematic parameters like the orientation, the angular velocities, and the accelerations. Gyroscopes provide good estimation of angular velocities, which are integrated versus time to get the orientation estimation of the sensor. However, due to the noise and the offset errors of the measured angular velocity, the integrated orientation drifts over time. Accelerometers and magnetometers are used to prevent the sensor orientation from drifting over time based on taking the gravitational acceleration and the earth magnetic field as references. Kalman Filters are used to fuse all these sensor outputs together for the optimized orientation estimation [72]. The working principle of the IMU is illustrated in Figure 3-5. The mathematics for the IMU orientation tracking algorithm can be found in [8, 9].

Figure 3-4: Functional diagram of IMU and its coordinate system

Besides providing the orientation of sensors with respect to the global frame, the IMU sensors can provide the kinematic measurements: acceleration measurement and the angular velocity, all with respect to the sensor body frame. They can be transformed into the global frame once the orientation of the IMU sensor is determined.

Figure 3-5: Orientation tracking algorithm of IMU

Acceleration

In the acceleration measurement $\mathbf{a}_f$, the sensor measures the sum of the acceleration $\mathbf{a}_s$, the gravity $\mathbf{g}_{f_s}$ in the sensor frame and also the white noise $\mathbf{w}_a$:

$$\mathbf{a}_f = \mathbf{a}_s - \mathbf{g}_{f_s} + \mathbf{w}_a. \quad (3-19)$$

Angular velocity

In angular velocity measurement $\boldsymbol{\omega}_m$, the sensor measures the sum of the angular velocity of the sensor $\boldsymbol{\omega}_s$, the offset $\mathbf{b}_s$ and the white noise $\mathbf{v}_\omega$.

$$\boldsymbol{\omega}_m = \boldsymbol{\omega}_s + \mathbf{b}_s + \mathbf{v}_\omega \quad (3-20)$$

The offset of the gyroscope $\mathbf{b}_s$ can be calibrated and removed during the factory calibration of the sensor components.

Orientation

The orientation also board to have some measurement errors due to the tracking inaccuracy. Let the measured orientation of the sensor be $\mathbf{R}_m$, and the actual measurement orientation be $\mathbf{R}_a$. There angular error can be represented by a rotation that correspond to an angular displacement $\delta\boldsymbol{\theta} \in \Re^{3 \times 1}$ such that

$$\mathbf{R}_m = e^{\delta\hat{\boldsymbol{\theta}}} \mathbf{R}_a. \quad (3-21)$$

Figure 3-6: IMU and wireless receivers

The probability distribution model of $\delta\theta = [\delta\theta_x, \delta\theta_y, \delta\theta_z]^T$ defines the inaccurate property of the IMU orientation measurement.

These models of the sensor measurements are useful in describing the uncertainty of the kinematics calculations as will be used in Chapter 5 and Chapter 6.

Type of IMUs in Use

Two types of IMU sensors are used in the study. The first type of IMU sensor is K-health sensors from the InterSense technology [72] as shown in Figure 3-6 (a). The second type of IMU is from APDM®, US [73] as shown in Figure 3-6 (b). These sensors are small in size so that it can be easily worn on the body without impeding the body motions. For these advantages with these small-size IMUs, the applications like walking, jogging, heel-to-toe walking, and jumping can be tracked easily. The specifications of the two types of sensors are listed in Appendix B. More details can be found in [72] and [73]. The APDM sensors have larger measurement range in acceleration and angular velocity compared with the K-Health sensor. Thus, its more suitable for measurements of dynamic motions.

Figure 3-7: Orientation sensors on the: lower limb, upper body, head.

Sensor Placement

As shown in Figure 3-7, for the lower limb measurement, the IMUs are attached on the pelvis and legs: One on the pelvis, and three for each leg attaching one the thigh, the shank and the foot respectively.

The mounting location of the sensor is important in general since it defines the relative displacement from the body coordinate frame to the sensor frame. All the sensors are attached where the skin and muscle movement is negligible in order to minimize the skin movement effects on the estimation accuracy.

With this concern in mind, the IMUs are mounted on the limbs very close to the bones where the skin movement is negligible. In this manner, the mapping between a body frame and its sensor frames can be considered as a constant matrix. In this dissertation, the sensor is only used for orientation measurement. Thus, the sensor does not need to be attachment to some exact locations. They can be attached in any comfortable posture since the mapping posture will be calibrated after the sensors are mounted on the body. Normally in the study, the IMU on the pelvis is mounted to the center point of two hip joints which is defined as the root point. The IMUs on the thighs are mounted slightly above the knee joint. On the shanks, IMUs are mounted slightly above the ankle joint. Foot IMUs are mounted on the face of the shoes.

For the upper limb motion, one IMU is attached to the back of the upper body to measure the upper body motion. For each arm, three IMUs are attached to the upper arm, the forearm and the hand respectively. They are also located on the arms where the skin and muscle effects are minimized. The upper arm IMU is mounted near to the elbow joint, while the forearm IMU is mounted near to the wrist. The hand IMU is mounted on the back of the hand. For the head motion, one IMU is attached to the forehead to measure the head motion when needed. If there is a hand-held gear (like the sword for kendo as demonstrated in Chapter 7), one IMU is attached on it to track its motion.

In the experimental study of the localization and tracking method, when the upper limb motion are not interested, eight IMUs are applied to for localization and tracking, the seven IMUs for the lower limbs as shown in Figure 3-7 and one for the chest.

After the sensor attachment, the system should be aware of the sensor positions in order to use the sensor measurements for human motion tracking.

Table 3-2: Notions of the parameters for body segments

Segments	Frame Name	Body Frame	Sensor Frame	Mappings (T, R)
Head	H1	f_{H1}	f_{H1S}	T_{H1M}, R_{H1M}
Trunk	U1	f_{U1}	f_{U1S}	T_{U1M}, R_{U1M}
Right Upper Arm	R4	f_{R4}	f_{R4S}	T_{R4M}, R_{R4M}
Right Forearm	R5	f_{R5}	f_{R5S}	T_{R5M}, R_{R5M}
Right Hand	R6	f_{R6}	f_{R6S}	T_{R6M}, R_{R6M}
Left Upper Arm	L4	f_{L4}	f_{L4S}	T_{L4M}, R_{L4M}
Left Forearm	L5	f_{L5}	f_{L5S}	T_{L5M}, R_{L5M}
Left Hand	L6	f_{L6}	f_{L6S}	T_{L6M}, R_{L6M}
Pelvis	f0	f_0	f_{0S}	T_{0M}, R_{0M}
Right Thigh	R1	f_{R1}	f_{R1S}	T_{R1M}, R_{R1M}
Right Shank	R2	f_{R2}	f_{R2S}	T_{R2M}, R_{R2M}
Right Foot	R3	f_{R3}	f_{R3S}	T_{R3M}, R_{R3M}
Left Thigh	L1	f_{L1}	f_{L1S}	T_{L1M}, R_{L1M}
Left Shank	L2	f_{L2}	f_{L2S}	T_{L2M}, R_{L2M}
Left Foot	L3	f_{L3}	f_{L3S}	T_{L3M}, R_{L3M}

3.4.2 Body Kinematics with Orientation Sensors

The sensor attached on the whole body is illustrated in Figure 3-8. The motion of each limb is measured by the sensor which is attached to the body segment. When using the orientation sensors to measure the body movements, the sensor measurements need to be recovered back to the human body motion.

Similar to the limb motion representation, each sensor needs a coordinate frame to describe its spatial motion. Here, f_i is used to define the body frame of limb i , and f_{is} is used to denote the frame for the corresponding sensors. The displacement of f_{is} with respect to f_i (the sensor position) is denoted by T_{iM} . All sensor frames and the corresponding parameters of the body segments are listed in Table 3-2.

Figure 3-9: Sensor attachments and the body coordinate frames.

As shown in Figure 3-9, the body segment frame is presented by f_i . The corresponding sensor frame is denoted by f_{is} . The relative displacement between them is denoted by T_{iM} ,

$$T_{iM} = \begin{bmatrix} R_{iM} & l_{iM} \\ \mathbf{0}_{1 \times 3} & 1 \end{bmatrix}. \quad (3-22)$$

where R_{iM} denotes the relative orientation between frame f_i and f_{is} ; l_{iM} denotes their relative displacement. Note that the sensor is tightly attached on the limb. Therefore, the values of T_{iM} are considered as constant. In this dissertation, only the relative orientation R_{iM} is considered because the actual location of the person in this study is not necessary.

Let T_i and T_{is} denote the orientation of the body and the sensor frame. Then, we have

$$T_{is} = T_i T_{iM}. \quad (3-23)$$

3.4.2.1 Sensor Motion to the Body Motion

In robotics, the motion of the joints can be directly measured from the encoders. However, in human motion tracking, the joint motions need to be calculated based on the wearable sensor measurements on the adjacent body segments.

Assume that the spatial displacement (with respect to the global frame) of sensor frame f_{is} at time t $T_{is}(t)$ can be obtained from sensor i . According to Figure 3-9, the body frame motion f_i at time t $T_i(t)$ can be calculated as follow,

$$T_i(t) = T_{is}(t) T_{iM}^{-1}. \quad (3-24)$$

Thus

$$\begin{aligned}
T_i &= \begin{bmatrix} \mathbf{R}_i & \mathbf{l}_{iB} \\ \mathbf{0}_{1 \times 3} & 1 \end{bmatrix} \\
&= \begin{bmatrix} \mathbf{R}_{iS} & \mathbf{l}_{iS} \\ \mathbf{0}_{1 \times 3} & 1 \end{bmatrix} \begin{bmatrix} \mathbf{R}_{iM} & \mathbf{l}_{iM} \\ \mathbf{0}_{1 \times 3} & 1 \end{bmatrix}^{-1} \\
&= \begin{bmatrix} \mathbf{R}_{iS} \mathbf{R}_{iM}^T & \mathbf{l}_{iS} - \mathbf{R}_{iS} \mathbf{R}_{iM}^T \mathbf{l}_{iM} \\ \mathbf{0}_{1 \times 3} & 1 \end{bmatrix}
\end{aligned} \tag{3-25}$$

The orientation of the body frame f_i , $\mathbf{R}_i$ can be obtained by

$$\mathbf{R}_i = \mathbf{R}_{iS} \mathbf{R}_{iM}^T, \tag{3-26}$$

and the body frame location with respect to global frame is

$$\mathbf{l}_{iB} = \mathbf{l}_{iS} - \mathbf{R}_{iS} \mathbf{R}_{iM}^T \mathbf{l}_{iM}, \tag{3-27}$$

where $\mathbf{l}_{iB}$ denotes the location of the body frame f_i , $\mathbf{l}_{iS}$ denotes the location of the corresponding sensor frame f_{iS} .

Denote the angular velocity of the body segment in body frame f_i by $\boldsymbol{\omega}_{i,b}$ and $\hat{\boldsymbol{\omega}}_{i,b}$ denotes the corresponding 3×3 skew-symmetric matrix. Denote the angular velocity of the body segment in the body frame f_{iS} by $\boldsymbol{\omega}_{i,S}$ and $\hat{\boldsymbol{\omega}}_{i,S}$ denotes the corresponding 3×3 skew-symmetric matrix.

Differentiating (3-24), we have: $\dot{T}_i(t) = \dot{T}_{iS}(t) T_{iM}^{-1}$. It is known that $\dot{\mathbf{R}}_i = \mathbf{R}_i \hat{\boldsymbol{\omega}}_i$ [74].

Thus, we have

$$\begin{aligned}
\begin{bmatrix} \mathbf{R}_i \hat{\boldsymbol{\omega}}_{i,b} & \dot{\mathbf{l}}_{iB} \\ \mathbf{0}_{1 \times 3} & 0 \end{bmatrix} &= \begin{bmatrix} \mathbf{R}_{iS} \hat{\boldsymbol{\omega}}_{i,S} & \dot{\mathbf{l}}_{iS} \\ \mathbf{0}_{1 \times 3} & 0 \end{bmatrix} \begin{bmatrix} \mathbf{R}_{iM} & \mathbf{l}_{iM} \\ \mathbf{0}_{1 \times 3} & 1 \end{bmatrix}^{-1} \\
&= \begin{bmatrix} \mathbf{R}_{iS} \hat{\boldsymbol{\omega}}_{i,S} & \dot{\mathbf{l}}_{iS} \\ \mathbf{0}_{1 \times 3} & 0 \end{bmatrix} \begin{bmatrix} \mathbf{R}_{iM}^T & -\mathbf{R}_{iM}^T \mathbf{l}_{iM} \\ \mathbf{0}_{1 \times 3} & 1 \end{bmatrix} \\
&= \begin{bmatrix} \mathbf{R}_{iS} \hat{\boldsymbol{\omega}}_{i,S} \mathbf{R}_{iM}^T & \dot{\mathbf{l}}_{iS} - \mathbf{R}_{iS} \hat{\boldsymbol{\omega}}_{i,S} \mathbf{R}_{iM}^T \mathbf{l}_{iM} \\ \mathbf{0}_{1 \times 3} & 0 \end{bmatrix}
\end{aligned} \tag{3-28}$$

Note that $\mathbf{R}_{iS} \hat{\boldsymbol{\omega}}_{i,S} \mathbf{R}_{iM}^T = \mathbf{R}_{iS} \mathbf{R}_{iM}^T (\mathbf{R}_{iM} \hat{\boldsymbol{\omega}}_{i,S} \mathbf{R}_{iM}^T) = \mathbf{R}_i (\mathbf{R}_{iM} \boldsymbol{\omega}_{i,S})^\wedge$ [74]. Thus,

$$\begin{bmatrix} \mathbf{R}_i \hat{\boldsymbol{\omega}}_{i,b} & \dot{\mathbf{l}}_{iB} \\ \mathbf{0}_{1 \times 3} & 0 \end{bmatrix} = \begin{bmatrix} \mathbf{R}_i (\mathbf{R}_{iM} \boldsymbol{\omega}_{i,S})^\wedge & \dot{\mathbf{l}}_{iS} - \mathbf{R}_i (\mathbf{R}_{iM} \boldsymbol{\omega}_{i,S})^\wedge \cdot \mathbf{l}_{iM} \\ \mathbf{0}_{1 \times 3} & 0 \end{bmatrix} \tag{3-29}$$

The angular velocity of the body in body frame i becomes

$$\hat{\boldsymbol{\omega}}_{i,b} = (\mathbf{R}_{iM} \boldsymbol{\omega}_{i,S})^\wedge = \mathbf{R}_{iM} \hat{\boldsymbol{\omega}}_{i,S} \mathbf{R}_{iM}^T, \tag{3-30}$$

Thus $\boldsymbol{\omega}_{i,b} = \mathbf{R}_{iM} \boldsymbol{\omega}_{i,S}$.

The linear velocity of the body frame i in the global frame becomes

$$\begin{aligned}
\dot{\mathbf{l}}_{iB} &= \dot{\mathbf{l}}_{iS} - \mathbf{R}_{iS} \mathbf{R}_{iM}^T (\mathbf{R}_{iM} \boldsymbol{\omega}_{i,S})^\wedge \cdot \mathbf{l}_{iM} \\
&= \dot{\mathbf{l}}_{iS} - \mathbf{R}_{iS} \hat{\boldsymbol{\omega}}_{i,S} \mathbf{R}_{iM}^T \mathbf{l}_{iM}
\end{aligned} \tag{3-31}$$

Differentiating both angular velocity and linear velocity, we obtain the angular acceleration in body frame i as

$$\dot{\boldsymbol{\omega}}_{i,b} = \mathbf{R}_{iM} \dot{\boldsymbol{\omega}}_{i,S}; \tag{3-32}$$

$$\hat{\dot{\boldsymbol{\omega}}}_{i,b} = (\mathbf{R}_{iM} \dot{\boldsymbol{\omega}}_{i,S})^\wedge = \mathbf{R}_{iM} \hat{\dot{\boldsymbol{\omega}}}_{i,S} \mathbf{R}_{iM}^T. \tag{3-33}$$

The acceleration of the body frame f_i in the global frame is

$$\begin{aligned}
\ddot{l}_{iB} &= \ddot{l}_{iS} - R_i R_{iM} \hat{\omega}_{i,S}^2 R_{iM}^T l_{iM} - R_i R_{iM} \hat{\omega}_{i,S} R_{iM}^T l_{iM} \\
&= \ddot{l}_{iS} - R_{iS} \hat{\omega}_{i,S}^2 R_{iM}^T l_{iM} - R_{iS} \hat{\omega}_{i,S} R_{iM}^T l_{iM} .
\end{aligned} \tag{3-34}$$

3.4.2.2 Joint Motion

After obtaining the velocity and acceleration of the body limbs, the body joint kinematics can be calculated subsequently. Joint displacement is the relative motion between the two adjacent limb segments, with respect to the initial posture. Let joint i to be the joint connecting the two adjacent limbs $i-1$ and i ; $T_{i-L,i}(0)$ the initial displacement of limb i and $T_{i-L,i}(t)$ the posture of the frame f_i with respect to f_{i-1} at instant t .

Let $e^{\hat{\xi}_i q_i}$ denote the twist motion of joint i . Then, it should satisfy the following condition,

$$T_{i-L,i}(t) = T_{i-L,i}(0) e^{\hat{\xi}_i(t) q_i(t)}. \tag{3-35}$$

Then we have

$$e^{\hat{\xi}_i q_i} = T_{i-L,i}^T(0) T_{i-L,i}(t). \tag{3-36}$$

The joint angular velocity describes the relative angular velocity between the body frame $i-1$ and i (with respect to the body frame f_{i-1}), which is denoted by $\omega_{J,i}$.

This angular velocity is presented in the body frame f_{i-1} ,

$$\begin{aligned}
\omega_{J,i} &= R_{i-L,i}(t) \omega_{i,b} - \omega_{i-L,b} \\
&= R_{i-L,i}(t) R_{iM} \omega_{i,S} - R_{i-L,M} \omega_{i-L,S}
\end{aligned} \tag{3-37}$$

Based on the proper calibrated human kinematic model and the captured motions of body segments and joints using the wearable sensors, the motion of the human

body is fully defined. After obtaining the kinematic parameters of the subjects, the kinetic parameters of the human body can be calculated based on the body kinetic model.

3.5 Simplified Kinetic Model

In human kinetics, useful kinetic parameters include contact forces, body joint reaction forces, joint torques, and the muscle/ligament strengths.

Table 3-3: Notation for human kinetics

Body frame	CG Location	Mass	Inertia frame	Inertia	Acceleration	Angular Acceleration
f_i	$l_{ic} (3 \times 1)$	$m_i (1 \times 1)$	$f_{i,I} (3 \times 1)$	$I_{i,I} (3 \times 3)$	$a_{i,I} (3 \times 1)$	$\alpha_{i,I} (3 \times 1)$
Joint Force	Joint Torque	Force From the Children Joints	Torque From the Children Joints	External Force	External Torque	
$F_i (3 \times 1)$	$\tau_i (3 \times 1)$	$F_{i+I} (3 \times 1)$	$\tau_{i+I} (3 \times 1)$	$F_{iE} (3 \times 1)$	$\tau_{iE} (3 \times 1)$	

The kinetics of the body can be modeled based on the Newton- Euler equation for the simplified human model as shown in Figure 3-10 with notions defined in Table 3-3.

All the parameters in Figure 3-10 and Table 3-3 are presented in the inertial frame $f_{i,I}$. The inertial matrix of body segment i is presented in this inertia frame $f_{i,I}$ by $I_{i,I}$.

Figure 3-10: Force and torque diagram

Let $\mathbf{F}_i$ denotes the joint force of joint i exerted on limb i and $-\mathbf{F}_{i+1}$ denotes sum of the other joint reaction forces that are exerted on the limb i . The gravity force acting on the limb i is $m_i \mathbf{g}$. $\mathbf{F}_{iE}$ is the external force. The inertial force is $-m_i \mathbf{a}_{i,I}$. According to the D' Alembert's principle [75], the force equilibrium equation on the limb segment i can be written as

$$\mathbf{F}_i - \mathbf{F}_{i+1} + \mathbf{F}_{iE} - m_i \mathbf{a}_{i,I} + m_i \mathbf{g} = 0. \quad (3-38)$$

Thus we have

$$\mathbf{F}_i = \mathbf{F}_{i+1} - \mathbf{F}_{iE} + m_i (\mathbf{a}_{i,I} - \mathbf{g}). \quad (3-39)$$

Let τ_i denotes the joint torque of joint i exerted on limb i and $-\tau_{i+1}$ denotes sum of the other joint reaction torques that are exerted on the limb i . The torques are

presented in the inertial frame $f_{i,I}$. The torque $\tau_I(F_i)$, $\tau_I(F_{i+I})$ and $\tau_I(F_{iE})$ are the torques generated by forces F_i , F_{i+I} and F_{iE} respectively. The inertial torque is $-I_{i,I}\alpha_{i,I}$. The external torque is τ_{iE} . According to the D' Alembert's principle, the torque equilibrium equation on the limb segment i can be written as

$$\tau_i - \tau_{i+I} + \tau_{iE} + \tau_I(F_i) + \tau_I(F_{i+I}) + \tau_I(F_{iE}) - I_{i,I}\alpha_{i,I} = 0. \quad (3-40)$$

Thus we have

$$\tau_i = \tau_{i+I} - \tau_{iE} - \tau_I(F_i) - \tau_I(F_{i+I}) - \tau_I(F_{iE}) + I_{i,I}\alpha_{i,I}. \quad (3-41)$$

Note that the force and torque is represented in the inertial frame $f_{i,I}$. Therefore, if the joint forces and torques need to be transformed into the body frame, a rotational transformation is needed. Let $R_{i,I}$ be the orientation of $f_{i,I}$ with respect to f_i . The force and torque of joint i in body frame f_i are denoted by $F_{i,b}$ and $\tau_{i,b}$. Then we have

$$\tau_{i,b} = R_{i,I} \cdot \tau_i, \quad (3-42)$$

$$F_{i,b} = R_{i,I} \cdot F_i. \quad (3-43)$$

Once the kinematics of the human body are fully captured, the joint forces and joint torques can be calculated based on the recursion algorithm starting from the distal limbs of the body [76]. As the human body normally provides interactions with the environment, the contact forces and torques are the external forces F_{iE} and torques τ_{iE} that need to be measured before using the force and torque equilibrium equations for the kinetic calculation.

Let $F_{i,S}$, $\tau_{i,S}$ denote the measured contact force and torque in the sensor frame of limb i ; $T_{i,S}$ denote the posture of the sensor in the global frame with $R_{i,S}$ and $l_{i,S}$

being the orientation and location of the sensor in the globe frame. The orientation of the force/ torque sensor attached on the body could be calculated based on the body kinematics.

Then the force/ torque of sensor i in the global frame $\mathbf{F}_{i,W}$ and $\boldsymbol{\tau}_{i,W}$ can be described as

$$\mathbf{F}_{i,W} = \mathbf{R}_{i,S} \mathbf{F}_{i,S}, \quad (3-44)$$

$$\boldsymbol{\tau}_{i,W} = \mathbf{R}_{i,S} \boldsymbol{\tau}_{i,S}. \quad (3-45)$$

Hence, a contact force/ torque measured by sensor i can be fully described as a triplet as follows.

$$\{\mathbf{T}_{i,S}, \mathbf{F}_{i,W}, \boldsymbol{\tau}_{i,W}\}, \quad (3-46)$$

where $\mathbf{T}_{i,S}$ represents the contact location and orientation in the global frame. $\mathbf{F}_{i,W}$ represents the contact force and $\boldsymbol{\tau}_{i,W}$ represents the contact torque, all with respect to the global frame f_W .

In the multi-contact situation, the contact forces balance the full body gravity and the inertial forces for accelerating and decelerating the whole body. Therefore, full body force equilibrium equation is

$$\sum_{i=1}^n \mathbf{F}_{i,W} + \sum_{j=1}^h m_j \cdot \mathbf{g} - \sum_{j=1}^h m_j \cdot \mathbf{a}_{j,W} = 0 \quad (3-47)$$

where $\sum_{i=1}^n \mathbf{F}_{i,W}$ is the sum of the contact forces. $\sum_{j=1}^h m_j \cdot \mathbf{g}$ is the sum of the gravity and $-\sum_{j=1}^h m_j \cdot \mathbf{a}_{j,W}$ is the sum of the inertial forces. Here, h denotes the number of the body segments.

Figure 3-11: Contact forces and torques

In torque equilibrium equation, the contact torque $\sum_{i=1}^n \tau_{i,W}$ and the torque generated by the contact force $\sum_{i=1}^n \mathbf{r}_{C_i} \times \mathbf{F}_{i,W}$ are to balance the internal torque $\sum_{j=1}^h (-\mathbf{I}_{j,W} \mathbf{a}_{j,W})$ and the torque generated by the inertial forces $\sum_{j=1}^h (-\mathbf{l}_{dC_j} \times m_j \mathbf{a}_{j,W})$. From the definition of CG (center of gravity), it is known that *the sum of torques* generated by the gravity at the whole body CG point is zero. Therefore, we define a CG frame whose origin is located at the whole body CG and the orientation of the frame is the same as the global frame f_w . Then, we have the torque equilibrium equation presented in the full body CG frame as

$$\sum_{i=1}^n (\tau_{i,W} + \mathbf{r}_{C_i} \times \mathbf{F}_{i,W}) + \sum_{j=1}^h (-\mathbf{I}_{j,W} \mathbf{a}_{j,W} - \mathbf{l}_{dC_j} \times m_j \mathbf{a}_{j,W}) = 0, \quad (3-48)$$

where $\mathbf{l}_{dC_j}$ denotes the vector from the body CG to the CG of the j -th limb segment. With the full body kinematics obtained, the CG location of the whole

body $\mathbf{p}_{cg}$ can be calculated based on the posture and mass properties of all the body segments as

$$\mathbf{p}_{cg} = \frac{\sum_{j=1}^h (m_j \cdot \mathbf{p}_{c_j})}{\sum_{j=1}^h m_j}, \quad (3-49)$$

where $\mathbf{p}_{c_j}$ is the CG position of the j -th limb segment and m_j is its mass.

Note that normally the inertial matrix of a limb j is presented in their inertial frame by $\mathbf{I}_{j,I}$. When presenting it in the global frame (with the same rotational center), the inertial matrix change to $\mathbf{I}_{j,W}$. Let $\mathbf{R}_{j,WI}$ denotes the orientation of the inertia frame of the limb j with respect to the global frame. Then we have [75]

$$\mathbf{I}_{j,W} = \mathbf{R}_{j,WI} \mathbf{I}_{j,I} \mathbf{R}_{j,WI}^T. \quad (3-50)$$

The force and the torque equations define the relationship between the multiple contacts and the body kinetics. After the body motion kinetic calculation, the body joint torque and joint reaction forces can be obtained [60-62].

Currently, accurately modeling the human kinetic model is still challenging because of the complexity of the human body with bones, muscles, skins and ligaments extra. The inertia and mass properties of the body are also not easy to measure. More importantly, due to the movements of the muscle and organs in the human body, the kinetic parameters are not constants. Normally, these parameters including the mass distribution, the moment of inertia are estimated using anthropomorphic data table of human [61, 77].

In many cases, people do not need the full kinetic tracking. For example, during the landing phase of the jumping when the feet contact the ground. The joint reaction forces at the knee joints are mainly resulted from the ground reaction force. The

inertial forces from the kinetic model of the human are relatively negligible. In these applications, the kinetic model of the human can be much simplified accordingly. By doing so, the computational efficiency will be much reduced and there will be less requirements on the wearable sensors since the unnecessary parameters does not needed to be measured in the simplified model.

3.6 Summary

This chapter introduces the kinematics and kinetics for the pHEI via wearable sensors. Following the hierarchy of the human body, the human kinematics is formulated using the POE method. The kinematics that processes the sensor motion to the body motion is discussed. Then the human kinetic model is also formulated.

This kinematic and kinetic model of the human body connects the sensor measurements with the human motion and interactions. The formulations of the human and sensor system are the basis for the body movement tracking, human kinematic parameter calibration and localization, as discussed in the following chapters. Therefore, the kinematic parameters including the limb dimensions and the mounting position of the sensors need to be determined to fully define the human kinematic model before conduction motion tracking. This process will be discussed in Chapter 4.

Chapter 4 Calibration of Human Kinematics Model via Wearable Sensors

The calibration of human kinematic model has two aspects for accurate motion capture. One is the calibration of the limb dimension parameters in the human kinematic model because the body kinematic model is different from person to person. The other is the wearable sensor position with respect to the body segment frame because they are needed to transform the sensor measurements into the limb segment motions for human body motion tracking.

In the human kinematic model calibration, the limb dimension parameters to be calibrated are listed in the last column of Table 3-1. For all kinds of human motion tracking systems, accurately measuring the skeleton dimensions of the human is an important and challenging issue. Although the optical based motion tracking technology can estimate the body dimensions of the subject by determining the center of rotation (COR) and axis of rotation (AOR) based on the statistical analysis of the position of the markers attached on the human body, the large number of markers and amount of data makes the estimation procedure very time consuming and complicated [78-80]. If the marker sets are not properly assigned, the result is usually inaccurate because of the skin movement effect and the COR estimation algorithms. The estimated skeleton model from the marker sets also has asymmetric problems. Also, the high price and limited capture volume of the optical motion capture systems make the optical based technology not feasible for daily use.

Some existing commercial inertial Motion Capture Systems determine the body skeleton dimensions based on the external measurement devices. Gypsy system measures the skeleton model by taking photos of the front and the side view of the subject. The picture is then post-processed through a software called AutoCAL to estimate the skeleton dimensions of the subject [6]. Brodie et al built a 3-D

anthropometry for skeleton dimensions measurement of human subjects [23, 24], as shown in Figure 4-1. It is time consuming for individuals to measure the whole body skeleton dimensions. Post-process of the data to generate the skeleton model also takes time.

In the sensor posture calibration, the relative posture between the limb segment's body frame and the corresponding sensor frame are determined. As discussed in Chapter 3, the initial posture of the body segment frames the defined by the bearing angle (the facing orientation) of the human subject's initial posture. In the calibration procedure of Gypsy 190 IMC systems of MetMotion and MVN of Xsens, the subjects is required to face north during the standing calibration posture [81] to have a known bearing angle. However the reference-north orientation is not always available for use. More importantly, after moving for a long time, the wearable sensors may shift slightly on the body segments. Recalibration of the system will be needed to correct the posture of the sensors. Therefore, a flexible and convenient calibration that can be conducted at any time is desired for the self-contained tracking systems.

In this chapter, a quick template based calibration method for human kinematic model based on the wearable orientation measurement sensors is introduced. Firstly in this method, the calibration of sensor positions with respect to the body segment frames is discussed. Then, the orientation measurement sensors are used to measure the posture of the limbs. A pre-defined template is used to confine the postures of the distal limbs, eg. feet and hands. By capturing the limb postures while the distal limbs match the given postures on the template, a system of linear kinematic equations of the limb dimensions can be formed. The limb dimension parameters are estimated based the set of the forward kinematic equations from the captured postures. The calibration examples and procedures are presented and validated.

Figure 4-1: The 3-D anthropometry frame, Brodie et al[23, 24]

4.1 Sensor Position Calibration

Sensors position calibration refers to the determination of the coordinate mappings from limb segment frame to the sensor frame, as listed in the last column of Table 3-2.

After attaching the sensors on the limbs, the coordinate mapping between the body segment frames and the corresponding sensor frames are fixed. It is known that the orientation sensors can measure their absolute orientation with respect to the global coordinate. Therefore, if the orientations of the body segments during the initial calibration posture are known, the sensor position (here we only consider the relative orientation) with respect to the corresponding body frames can be calculated. From Section 3.2, we known that in an initial standing posture, the posture of the body frames are defined based on the body bearing angle. Therefore, this method first determines the bearing angle of the subject. The sensor positions

in their body segment frames are determined subsequently. This is the principle of the sensor position calibration.

This calibration consists of two simple steps as shown in Figure 4-2.

Step 1: After wearing all the sensors on the corresponding body segments, the subject stands straight in an initial standing posture. Then, the subject keeps standing straight for five seconds so as to record sensor data in the computer. To control the distance and angle between two feet, a board with a pair of pre-designed footprints can be used as illustrated in Figure 4-10 later. The subject stands still with two feet matching the footprints.

Step 2: The subject stoop down in the forward direction as shown in Figure 4-2 and keep the posture for five seconds for the computer to record the stoop posture.

Figure 4-2: Sensor posture calibration

In the calibration process as shown in Figure 4-2, the IMU attached on the upper body only rotates about the Y-axis of the initial body frame. Let $\mathbf{R}_{s1}$ represent the rotation matrix of the upper body in the standstill posture with respect to the global frame f_w . The rotation matrix of the upper body in the stoop posture with respect to f_w is represented by $\mathbf{R}_{s2}$. The relative rotation matrix from the standstill posture to the stoop posture $\mathbf{R}_{s12}$ becomes

$$\mathbf{R}_{s12} = \mathbf{R}_{s1}^T \mathbf{R}_{s2}. \quad (4-1)$$

Then, this rotational axis of the upper body (the axis along the Y direction) can be identified by extracting the rotation axis of $\mathbf{R}_{s12}$ during the motion. The algorithm as follows. In this rotation, the direction of the rotation axis in the global frame denoted by $r_{s12,W}$ can be obtained by

$$\begin{aligned} r_{s12,W} &= \mathbf{R}_{s1} r_{s12,B} \\ &= \mathbf{R}_{s1} Sc(\mathbf{R}_{s12}) \quad , \\ &= (x_{s12}, y_{s12}, z_{s12}) \end{aligned} \quad (4-2)$$

where $Sc(\mathbf{R}_{s12})$ is a function extracting the rotation axis of the rotation matrix $\mathbf{R}_{s12}$ in the local body frame denoted by $r_{s12,B}$ [10, 72].

Let $\mathbf{S} = \mathbf{R}_{s12} - \mathbf{R}_{s12}^T$. According to [10, 72], $\mathbf{S}$ is in the form of a 3×3 skew-symmetric matrix of the form:

$$\mathbf{S} = \begin{bmatrix} 0 & -s_3 & s_2 \\ s_3 & 0 & -s_1 \\ -s_2 & s_1 & 0 \end{bmatrix} \quad (4-3)$$

The directional vector of the rotation axis in the local frame can be calculated as

$$\mathbf{r}_{s12,B} = \frac{1}{\sqrt{s_1^2 + s_2^2 + s_3^2}} [s_1, s_2, s_3]^T \quad (4-4)$$

Then, pre-multiply $\mathbf{R}_{sI}$ to convert it from the local frame to the global frame as shown in Equation (4-2).

At the initial standing posture as shown in Figure 4-2, the angular displacement between the root frame and the global frame contains only the bearing along the Z-axis of f_w (The bearing angle is zero if the subject face north). The bearing of the subject can be determined by calculating the angle between the Y-axes of the global frame f_w and the initial upper body frame f_{U1} .

Figure 4-3: Bearing angle of the initial standstill posture

From Figure 4-3, it is clear that the bearing angle of the body can be calculated by

$$\Phi = -\text{atan } 2(x_{s12}, y_{s12}), \quad (4-5)$$

$$\text{where } \text{atan } 2(a, b) = \begin{cases} \arctan(a / b), & b > 0 \\ \arctan(a / b) + \pi, & a > 0, b < 0 \\ \arctan(a / b) - \pi, & a < 0, b < 0 \\ \pi / 2, & a > 0, b = 0 \\ -\pi / 2, & a < 0, b = 0 \end{cases}$$

Figure 4-4: Notation for the calibration model of body dimensions.

In the initial standard posture with the bearing angel Φ , the body segment frames are all in the same orientation, the same as the upper body frame. The rotation matrix from the global frame to every limb segment frame can be written as

$$\mathbf{R}_i = \text{rot}_z(\Phi) \quad (4-6)$$

where function $\text{rot}_z(\Phi)$ provide the rotational matrix of rotating around the Z axis with angle Φ .

Then, we can calculate the mapping from each body segment frame to the corresponding sensor frame using the recorded initial standing posture data $\mathbf{R}_i$ according to section 3.4.2.1 by

$$\mathbf{R}_{iM} = \mathbf{R}_i^T \mathbf{R}_{iS} . \quad (4-7)$$

As the location of the orientation measurement sensors may shift slightly for long duration movements, recalibration of the mapping between sensors and body

segment frames is necessary. The proposed method can recalibrate the sensor mapping anywhere without additional devices and references.

After calibration the sensor positions, the posture of the body limbs can be measured. The calibration of the body dimensions can be conducted accordingly.

4.2 Calibration Model of Body Dimensions

In calibration of body dimensions, the limb segment dimensions are the parameters to be determined, as shown in the last column of Table 3-1.

In order to have a general calibration model for both lower limb and upper limb dimensions and also for other types of kinematic systems, a general calibration model is defined as shown in Figure 4-4, with link $0 \rightarrow 1, 1 \rightarrow 2, \dots, (n-2) \rightarrow (n-1), (n-1) \rightarrow (n)$ being the series of limbs to be calibrated. Let the orientation of the link $(i-1) \rightarrow (i)$ with respect to the global reference frame be $\mathbf{R}_{0,i}$, and its dimension parameter $l_{i-1,i}$. The links $(i-1) \rightarrow (i)$ and $(i) \rightarrow (i+1)$ are connected through a joint i whose rotational motion is denoted by $\mathbf{R}_{i-1,i}$. The example of lower limb calibration model is shown in the right of Figure 4-4.

In the template-based human kinematic calibration procedure, the wearable orientation sensors measure the postures $\mathbf{R}_{0,i}$ of the limb segments. The footprint / handprint template is used to confine the location of the distal limbs, eg. the feet for the lower limb calibration, and the hands for the upper arm calibration. The relative posture of the two distal limbs denoted as $\mathbf{p}_{st}$ is defined by the templates as shown in Figures 4-10 and 4-14 later.

Referring to Equation (3-9), and note that $\prod_{i=1}^k \mathbf{R}_{i-1,i} = \mathbf{R}_{0,k} \cdot \mathbf{R}_{0,k}$ denotes the orientation of the body frame k with respect to the reference frame. Then, $\mathbf{p}_{st}$ becomes,

$$\mathbf{p}_{st} = \mathbf{R}_{0,1}\mathbf{l}_{0,1} + \mathbf{R}_{0,2}\mathbf{l}_{1,2} + \dots + \mathbf{R}_{0,n}\mathbf{l}_{n-1,n} \quad (4-8)$$

Combining all the limb dimension parameters as the unknown parameters, the above equation can be expressed as follows.

$$\mathbf{y} = \mathbf{A}_i \mathbf{x}. \quad (4-9)$$

where $\mathbf{y} = \mathbf{p}_{st} \in \Re^{3 \times 1}$,

$$\mathbf{A}_i = [\mathbf{R}_{0,1}, \mathbf{R}_{0,2}, \dots, \mathbf{R}_{0,n}] \in \Re^{3 \times 3n},$$

$$\text{and } \mathbf{x} = [\mathbf{l}_{0,1}^T, \mathbf{l}_{1,2}^T, \mathbf{l}_{2,3}^T, \dots, \mathbf{l}_{n-1,n}^T]^T \in \Re^{3n \times 1}$$

In the calibration model, $\mathbf{l}_{0,1}, \mathbf{l}_{1,2}, \mathbf{l}_{2,3}, \dots, \mathbf{l}_{n-1,n}$ are the parameters to be calibrated.

Therefore, if we match (m) postures with known positions of the distal limbs $\mathbf{p}_{st}$, we can have a linear equations system as follows.

Figure 4-5: Illustration of lower limb calibration using eight calibration postures.

$$\begin{aligned}
Y &= \tilde{A}x, \\
Y &= [y_1^T, y_2^T, \dots, y_m^T]^T \in \mathfrak{R}^{1 \times 3m}, \quad . \\
\tilde{A} &= [A_1^T, A_2^T, \dots, A_m^T]^T \in \mathfrak{R}^{3m \times 3n}
\end{aligned} \tag{4-10}$$

In order to better illustrate the calibration method, an example of calibrating the lower limb dimensions using eight calibration postures is shown in Figure 4-5. For the lower limb, without considering the symmetric property of the limbs, there are five limbs whose dimensions need to be calibrated: The right shank (link 0→1), the right thigh (link 1→2), the pelvis (link 2→3), the left thigh (link 3→4) and the left shank (link 4→5). Then we have the calibration model as follows.

For one calibration posture, we have

$$\begin{aligned}
y &= p_{st} \in \mathfrak{R}^{3 \times 1} \\
A_i &= [R_{0,1}, R_{0,2}, R_{0,3}, R_{0,4}, R_{0,5}] \in \mathfrak{R}^{3 \times 15} . \\
x &= [l_{0,1}^T, l_{1,2}^T, l_{2,3}^T, l_{3,4}^T, l_{4,5}^T]^T \in \mathfrak{R}^{15 \times 1}
\end{aligned} \tag{4-11}$$

For all eight calibration postures, we have

$$\begin{aligned}
Y &= \tilde{A}x \\
Y &= [y_1^T, y_2^T, \dots, y_8^T]^T \in \mathfrak{R}^{1 \times 24} . \\
\tilde{A} &= [A_1^T, A_2^T, \dots, A_8^T]^T \in \mathfrak{R}^{24 \times 15}
\end{aligned} \tag{4-12}$$

Geometrically speaking, if we know the orientation of the limbs and we know the distance between the two distal limbs, it is possible to solve out the limb dimensions based on the closure equation of enough calibration postures.

In the first place, the posture number m should be at least more than the number of limbs so that the number of rows in matrix $\tilde{A}$ is more than the column. Otherwise, the constraint equations are not enough to solve the dimension parameters.

However, even when $m > n$, there are still conditions to be satisfied in order to make the dimension parameters solvable.

It is mentioned in [68] that if the column of $\tilde{A}$ is independent, the dimension parameters $\mathbf{x}$ can be solved out using the least square method. Thus, the skeleton model is calibrated to satisfy the least square errors in the target posture sets as shown in Equation (4-13).

$$\{\forall \mathbf{x} \in \Re^{3n \times 1} \mid \sum_{i=1}^m (\mathbf{y}_i - \mathbf{A}_i \mathbf{x}^*)^2 < \sum_{i=1}^m (\mathbf{y}_i - \mathbf{A}_i \mathbf{x}_i)^2\}, \quad (4-13)$$

where $\mathbf{x}^*$ denotes the calibrated limb dimension parameters.

This means that the calculated skeleton model solution will have a best fit to the target positions in the template compared with all other possible dimension parameters. Therefore, the more the number of calibration postures, the more accurate is the calibration parameters.

The solution is

$$\mathbf{x} = (\tilde{A}^T \tilde{A})^{-1} \tilde{A}^T \mathbf{Y}. \quad (4-14)$$

However, if a column of $\tilde{A}$ is the linear combination of other columns, these parameters are not solvable because in this case, $\tilde{A}^T \tilde{A}$ becomes a singular matrix. This is because, if a column of $\tilde{A}$ is dependent on the other columns. Then, there exists an invertible elementary column operations matrix $\mathbf{B}$ (and $\mathbf{B}$ is a $3m \times 3m$ matrix) such that the elements of one column (i) of $\tilde{A}\mathbf{B}$ are all zero. Then, it is easy to notes that $\mathbf{B}^-(\tilde{A}^T \tilde{A}) \mathbf{B} = (\tilde{A}\mathbf{B})^T (\tilde{A}\mathbf{B})$ is a *similarity transformation* of matrix $\tilde{A}^T \tilde{A}$ [82]. And notice that the determinant of $\mathbf{B}^-(\tilde{A}^T \tilde{A}) \mathbf{B}$ is zero. Thus we have

$$\det(\tilde{A}^T \tilde{A}) = \det(\mathbf{B}^-(\tilde{A}^T \tilde{A}) \mathbf{B}) = 0. \quad (4-15)$$

Therefore, in the next section, we discuss the solvable conditions of the human kinematic model.

4.3 Solvability of the Calibration Parameters

As shown in the calibration model, the matrix $\tilde{A}^T \tilde{A}$ needs to be invertible in order to solve out the dimension parameters of the human kinematics model.

In order to calibrate the limb dimension parameters, any column of A_i should not always be the same linear combination of other columns [68]. Denote first, second and third column by $x_{0,i}, y_{0,i}, z_{0,i}$, which is actually the direction vector of the X-Y-Z axes' of f_i in the global frame. Then, its 3 by 3 rotation matrix can be expressed by $R_{0,i} = [x_{0,i}, y_{0,i}, z_{0,i}]$. Then, $A_i = [[x_{0,1}, y_{0,1}, z_{0,1}], [x_{0,2}, y_{0,2}, z_{0,2}], \dots, [x_{0,n}, y_{0,n}, z_{0,n}]]$.

The relationship between the orientations of two adjacent limbs is $R_{0,i} = R_{0,i-1} R_{i-1,i} = R_{0,i-1} e^{\hat{\omega}_i q_i}$, where $e^{\hat{\omega}_i q_i}$ denotes the twist motion of joint i with q_i being the joint displacement as illustrated in Figure 4-6.

Figure 4-6: Single DOF joint motion

If there is a single DOF (hinge) joint i connecting the limb segment i and $i-1$ in the kinematic chain to be calibrated, then it is clear that the rotational axis has a constant coordinate in both body frame f_{i-1} and f_i . Let $\mathbf{u}_{i-1}$ and $\mathbf{u}_i$ denotes the constant coordinate (3×1 column vector) of the directional vector of the rotational axis in frame f_{i-1} and f_i . Then, when presenting this vector in the global frame, we have

$$\mathbf{R}_{0,i}\mathbf{u}_i = \mathbf{R}_{0,i-1}\mathbf{u}_{i-1}, \quad (4-16)$$

$$\text{or, } x_{u_i}\mathbf{x}_{0,i} + y_{u_i}\mathbf{y}_{0,i} + z_{u_i}\mathbf{z}_{0,i} = x_{u_{i-1}}\mathbf{x}_{0,i-1} + y_{u_{i-1}}\mathbf{y}_{0,i-1} + z_{u_{i-1}}\mathbf{z}_{0,i-1}, \quad (4-17)$$

where $\mathbf{u}_i = [x_{u_i}, y_{u_i}, z_{u_i}]^T$ and $\mathbf{u}_{i-1} = [x_{u_{i-1}}, y_{u_{i-1}}, z_{u_{i-1}}]^T$. They are all constants.

This means that the columns $\mathbf{x}_{0,i}, \mathbf{y}_{0,i}, \mathbf{z}_{0,i}, \mathbf{x}_{0,i-1}, \mathbf{y}_{0,i-1}, \mathbf{z}_{0,i-1}$ of matrix $\mathbf{A}_i$ are always linear dependent with the same relationship, and the same relationship also applies to matrix $\tilde{\mathbf{A}}$. According to Section 4.2, we know that in this situation, the dimensional parameters are not solvable because the matrix $\tilde{\mathbf{A}}^T \tilde{\mathbf{A}}$ is singular.

Figure 4-7: Uncertain skeleton model with single DOF joint: Lower limb example

Figure 4-8: Unique skeleton model with multiple DOF joint: Lower limb example

Geometrically, the case of the existence of hinge joints is illustrated in Figure 4-7. Because the location of the hinge joint center can shift along the joint axis direction without affecting the position of the ends in the kinematic chain, there is no unique solution for the kinematic model in this situation. However, if there is one more rotational DOFs in the joint. Thus, the problem will be avoided because the shifting distance along the first rotational axis will be different in the location of the end point after rotating along the second rotational axis.

Therefore, if none of the joints in the model is a single DOF (hinge) joint, the problem illustrated in Figure 4-7 will be avoided. In such cases, the X-Y-Z axes of each frame can change with their joint angles independently. Therefore, none of the frame axes is a constant linear combination of the other axes in this situation. The columns are not always with the same linear relationship. The $\tilde{\mathbf{A}}^T \tilde{\mathbf{A}}$ can be invertible based on a set of calibration postures.

To better explain this, it is understandable that in Figure 4-8 if there is one additional rotation DOF perpendicular to the hinge joint, the location of the joint center will be uniquely defined because the different skeleton models in Figure 4-7

will show differences at the position of the distal limb after rotating about the joint axis 2.

In the human skeleton model, for example, the knee joint is a one-DOF-joint. However, since the shank IMU is mounted near to the ankle joint, the pronation and supination of the shank provides an additional DOF to the knee joint which can be detected using the IMU. Therefore, the lower limb dimensions can be calibrated based on this method provided the shank is not only rotating along the knee joint. This is a requirement for the set of calibration postures.

This method can be used for the skeleton dimension calibration. However, using this model will not guarantee that the model will be symmetric on the right and the left sides. Therefore, in order not to have asymmetric human skeleton model after calibration, the symmetry of the human skeleton model needed to be taken into count.

4.4 Calibration of Symmetric Model

Figure 4-9: Lower limb calibration model.

For a healthy human subject, the skeleton model has symmetric property between corresponding limbs on the left and right sides. (The left thigh and the right thigh, the left shank and the left shank, the left forearm and the right forearm and the left upper arm and the right upper arm and so on). The symmetry is also a very useful feature to reduce the number of unknown parameters. To make the presentation clear to understand, we use the lower limb kinematic model to formulate the calibration model. The calibration models of other type of mechanism with different number of body limbs can be modified accordingly.

In human lower limb calibration model, the dimensions of the thigh, the shank and the distance between the two hips are the parameters to be calibrated, as shown in Figure 4-9. In the calibration model, $l_{0,1} = -r_{R2}, l_{1,2} = -r_{R1}, l_{2,3} = -2r_{R0} = 2r_{L0} \cdot l_{3,4} = r_{L1}, l_{4,5} = r_{L2} \cdot R_{0,1}, R_{0,2}, R_{0,3}, R_{0,4}, R_{0,5}$ represent the orientations of the right shank, the right thigh, the pelvis, the left thigh and the left shank respectively.

According to the symmetry of body parts based on the body coordinate definition, we known that the local coordinate of the corresponding body limbs are the same in the X and Z direction, and opposite in the Y direction. Then according to Figure 4-9, we have

$$l_{0,1} = Sl_{4,5}, l_{1,2} = Sl_{3,4}, \text{ where } S = \begin{bmatrix} -1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & -1 \end{bmatrix} \in SO(3). \quad (4-18)$$

Then according to section 4.2, the displacement between two feet becomes

$$p_{st} = (R_{0,1} + R_{0,5}S)l_{0,1} + (R_{0,2} + R_{0,4}S)l_{1,2} + R_{0,3}l_{2,3}. \quad (4-19)$$

Rearranging the equation, we have

$$\mathbf{y}' = \mathbf{A}'_i \mathbf{x}, \quad (4-20)$$

where $\mathbf{A}' = [(\mathbf{R}_{0,1} + \mathbf{R}_{0,5}\mathbf{S}), (\mathbf{R}_{0,2} + \mathbf{R}_{0,4}\mathbf{S}), \mathbf{R}_{0,3}]$, and $\mathbf{x}' = [\mathbf{l}_{0,1}^T, \mathbf{l}_{1,2}^T, \mathbf{l}_{2,3}^T]^T$.

Then the skeleton model can be calibrated based on this model after capturing the calibration postures. This method reduces the number of calibration parameters from fifteen to nine. Also, the calibrated model will be symmetric on the right and left side.

4.5 Human Kinematic Model Calibration

4.5.1 Lower Limb Calibration with IMU Sensors.

To use this calibration model to determine the dimensions of the lower limbs, it is still possible to reduce the number of calibration parameters. Since the vector $\mathbf{l}_{2,3}$ is along the lateral direction (Y-axis) of the body in the initial standing pose, we have $\mathbf{l}_{2,3} = [0, y_{2,3}, 0]^T$. Then, the calibration model is simplified as follows.,

$$\begin{aligned} \mathbf{A}'_i &= [(\mathbf{R}_{0,1} + \mathbf{R}_{0,5}\mathbf{S}), (\mathbf{R}_{0,2} + \mathbf{R}_{0,4}\mathbf{S}), \mathbf{y}_{0,3}] \in \Re^{3 \times 7} \\ \mathbf{x} &= [x_{0,1}, y_{0,1}, z_{0,1}, x_{1,2}, y_{1,2}, z_{1,2}, y_{2,3}]^T \in \Re^{7 \times 1}, \quad (4-21) \\ \mathbf{l}_{0,1} &= [x_{0,1}, y_{0,1}, z_{0,1}]^T, \mathbf{l}_{1,2} = [x_{1,2}, y_{1,2}, z_{1,2}]^T, \mathbf{l}_{2,3} = [0, y_{2,3}, 0]^T \end{aligned}$$

where $\mathbf{y}_{0,3}$ denotes the column 2 of $\mathbf{R}_{0,3}$. In this manner, the dimensions of the matrixes in the calibration model are reduced from 9 to 7.

4.5.1.1 Lower Limb Calibration Protocol

In the experiment, we use the wearable IMU sensors to calibrate the skeleton dimensions of the lower limbs. Here we use the footprint template to define the relative poses of the feet for different postures. In this way, when the subject matches the feet on the pre-designed footprints, their relative positions are defined.

Subsequently, with the measured orientation of limbs and the known position of the feet, the skeleton dimension can be calibrated.

In the footprint template, there are two positions available for the left foot and eight positions available for the right foot as shown in Figure 4-10. In the footprint template all eleven footprints are properly arranged within a flat area. For an adult, the distance between the two feet while standing straight is around 20cm in the footprint template. The distance between the adjacent footprints is thus 20cm along both the X- and the Y-direction. Different sizes of the footprint are printed together for users of different foot sizes. When both feet match the desired footprints, the vector from the left foot to the right foot is known as the vector from the left footprint center to the right footprint center. Here the “center” point of each foot is an estimation of the projection of ankle joints when the footprint is matched. Therefore, the vector $\mathbf{p}_{st}$ presents the relative position between two ankles.

Figure 4-10: Lay out of the footprint template

Figure 4-11: Lower limb calibration

After putting on all wearable sensors on the body, the calibration can be conducted. The complete procedures are simply several footprints matching steps which can be completed within a few minutes. The orientation mappings from body to sensor frames are first calibrated as discussed in Section 0 [83]. Then, the calibration procedure can be conducted.

Step 0: Sensor mapping calibration as introduced in Section 0.

Step 1: The subject locates his left and right feet in footprint L1 and footprint (1) separately, stands in the initial standing posture and keeps stationary for a few seconds to register this posture into the computer as shown in Figure 4-11.

Step 2: The subject keeps the left foot in stationary and matches his right foot with footprint (2) and keeps stationary for a few seconds to register this posture into the computer.

Step 3: Choose footprints from (3), (4),..., , and register the matching posture one by one in the same way as described in **Step 2**.

4.5.1.2 A Calibration Example

After the calibration procedure, the skeleton dimensions are determined based on the calibration model. Four subjects (Height: 178cm, 175cm, 173cm, 169cm) have been involved in the calibration and localization experiment. Here, the calibration result of one human subject's skeleton model (Height: 178cm) is provided as an example.

As a comparison, the model is first estimated through directly measuring the limb lengths of the body segments using the ruler. The measured lower limb lengths and the calibrated skeleton dimension results are provided in Table 4-1

The accuracy of the calibrated model can be seen from how well the calculated results can match the actual reference footprints on the template based on the forward kinematics calculation. In order to validate the accuracy of the calibrated human kinematic model, after the skeleton dimension calibration,

Table 4-1 Lower limb skeleton model (Limb vectors in local frame)

Name	Measured (m)	Calibrated (m)
Pelvis ($2r_{L0}$)	(0, -0.23, 0)	(0, -0.249, 0)
Right Thigh (r_{R1})	(0, 0, 0.49)	(-0.052, -0.0113, 0.471)
Right Shank (r_{R2})	(0, 0, 0.45)	(-0.049, -0.0107, 0.438)
Left Thigh (r_{L1})	(0, 0, 0.49)	(-0.052, 0.0113, 0.471)
Left Shank (r_{L2})	(0, 0, 0.45)	(-0.049, 0.0107, 0.438)

(1). The subject matches 15 footprint pairs and the postures are registered to the computer.

(2). The stride vectors are calculated based on the measured and the calibrated skeleton model separately.

The results are shown in Figure 4-12. The blue circle represents the reference location on the template. The red star represents the results from the direct measured skeleton model, and the red circle represents the results from the calibrated model. The RMS error of the 15 footprint locations from the measured model is (0.044, 0.023, 0.039) m, while the RMS error of the 15 footprint locations from the calibrated model is (0.0115, 0.0131, 0.0083) m. It is noticed that the footprint location result calculated based on the calibrated model tally better than that of the measured model.

Successful footprint template matching shows the validity of the proposed calibration method.

Figure 4-12: Calculated right foot location before/ after calibration

Figure 4-13: Upper limb calibration model.

It is also important to know the absolute accuracy of the calibrated skeleton dimensions. In other word, how much is the error in the skeleton dimension estimation. From Equation (4-14), we have:

$$\begin{aligned} \delta \mathbf{x} &= (\tilde{\mathbf{A}}^T \tilde{\mathbf{A}})^{-1} \tilde{\mathbf{A}}^T \cdot \delta \mathbf{Y} \\ \delta \mathbf{x} &= [\delta x_{0,1}, \delta y_{0,1}, \delta z_{0,1}, \delta x_{1,2}, \delta y_{1,2}, \delta z_{1,2}, \delta y_{2,3}]^T \end{aligned} \quad (4-22)$$

It means that the dimension error can be estimated based on the foot location errors and the corresponding matrix $\tilde{\mathbf{A}}$. $\delta \mathbf{Y} = [\delta y_1^T, \delta y_2^T, \dots, \delta y_n^T]^T$, where δy_i is the column vector of the position error between the calculated foot position using the skeleton model before calibration and the reference position on the template. Based on the footprint matching results, the estimated dimension errors of the measured and calibrated model are δx_m and δx_c separately:

$$\delta \mathbf{x}_m = [-0.047, 0.012, -0.021, -0.053, 0.0092, -0.018, 0.051]^T,$$

$$\delta \mathbf{x}_c = [-0.0093, -0.0082, -0.012, 0.0053, -0.0022, -0.0078, 0.011]^T.$$

In $\delta \mathbf{x}_c$, the dimension errors are controlled within one cm after the calibration. This accuracy level also applies to the other three subjects.

4.5.2 Upper Arm Calibration

In human upper limb calibration model, the dimension of the upper arm, the forearm and the distance between the two shoulder are the parameters to be calibrated (in this simplified model, we do not consider the motion of the collarbones) as shown in Figure 4-13. In the calibration model, $\mathbf{l}_{0,1} = -\mathbf{r}_{R5}$, $\mathbf{l}_{1,2} = -\mathbf{r}_{R4}$, $\mathbf{l}_{2,3} = -2\mathbf{r}_{TR} = 2\mathbf{r}_{TL}$, $\mathbf{l}_{3,4} = \mathbf{r}_{L4}$, $\mathbf{l}_{4,5} = \mathbf{r}_{L5}$. $\mathbf{R}_{0,1}$, $\mathbf{R}_{0,2}$, $\mathbf{R}_{0,3}$, $\mathbf{R}_{0,4}$, $\mathbf{R}_{0,5}$ represent the orientations of the right forearm, the right upper arm, the chest, the left upper arm and the left forearm respectively. The vector $\mathbf{l}_{2,3}$ is along the lateral direction of the body in the initial standing pose, $\mathbf{l}_{2,3} = [0, y_{2,3}, 0]^T$. Thus, the calibration model is the same as that of the lower limb:

$$\begin{aligned} \mathbf{A}' &= [(\mathbf{R}_{0,1} + \mathbf{R}_{0,5}\mathbf{S}), (\mathbf{R}_{0,2} + \mathbf{R}_{0,4}\mathbf{S}), y_{0,3}] \in \Re^{3 \times 7} \\ \mathbf{x} &= [x_{0,1}, y_{0,1}, z_{0,1}, x_{1,2}, y_{1,2}, z_{1,2}, y_{2,3}]^T \in \Re^{7 \times 1} \\ \mathbf{l}_{0,1} &= [x_{0,1}, y_{0,1}, z_{0,1}]^T, \mathbf{l}_{1,2} = [x_{1,2}, y_{1,2}, z_{1,2}]^T, \mathbf{l}_{2,3} = [0, y_{2,3}, 0]^T \end{aligned} \quad (4-23)$$

The hand mark template for the upper arm calibration is shown in Figure 4-14.

The template is fixed on a table in front of the subject and in parallel with the Y-axis of the human body. As the full-body sensor posture has already been calibrated during the coordinate mapping calibration, the upper limb calibration protocol is stated as follows.

Figure 4-14: Lay out of the hand mark template

Step 1: The subject matches his left hand (at the wrist joint) with hand mark L1, and his right hand (at the wrist joint) with hand mark (1) and keeps stationary for 5 to10 seconds to register this posture into the computer as shown in the left of Figure 4-15.

Step 2: The subject keeps the left hand in stationary and unfolds his right hand to match it with hand mark No. 2 and keeps stationary for 5 to10 seconds to register this posture into the computer as shown in the right of Figure 4-15

Figure 4-15: Upper limb calibration

Step 3: Match the other handprints (2, 3,..., 8, 9) in the same way as described in Step 2.

Note that the collarbone motion is not considered in our simplified human kinematic model. Thus, during the upper limb calibration, *the subject should not move the collarbone while matching the hand marks*. During the hand mark matching, the wrist is matched at the hand marks on the template.

The measured upper limb lengths using a ruler and the calibrated skeleton dimension results of the example subject are provided in Table 4-2.

Based on the hand mark matching result, the accuracy of the upper limb dimension calibration results is also within one centimeter accuracy.

Table 4-2 Upper limb skeleton dimension model

Name	Measured (m)	Calibration (m)
Shoulder breadth ($2r_{TL}$)	(0, -0.38, 0)	(0, -0.376, 0)
Right Upper Arm (r_{R4})	(0, 0, 0.28)	(-0.006, 0.0204, 0.290)
Right Forearm (r_{R5})	(0, 0, 0.26)	(-0.006, 0.0156, 0.255)
Left Upper Arm (r_{L4})	(0, 0, 0.28)	(-0.006, -0.0204, 0.290)
Left Forearm (r_{L5})	(0, 0, 0.26)	(-0.006, -0.0156, 0.255)

After the dimensions of the upper and lower limbs are determined, the dimension parameters of the chest, the head as well as the feet and hands also need to be estimated for a full body kinematic model.

4.5.3 Chest and Head

In presentation of head and trunk motions in most of the applications, their orientations are usually important. Their dimensions (and the dimension of the

hands and feet) can be estimated from the height of the subject based on anthropomorphic data table [77]. Except for the biomedical study of the trunk and the spine motions where more detail anatomy skeleton model of the spine or the neck is needed, the head and trunk dimension estimations from anthropomorphic data can be acceptable for most of the daily applications. Therefore, these parameters are only estimated rather than calibrated in this study.

In the full-body calibration, the sensor posture (coordinate mapping) is first calibrated. Then, the lower limb calibration based on the footprint template is conducted. Then follows the upper limb calibration based on the hand mark template. With known height of a subject, the dimensions such as the head, the foot and the hands are estimated based on the anthropomorphic data. In this way, the calibration of the full-body skeleton dimensions and the sensor locations are quickly carried out within a few minutes.

4.6 Summary

This chapter introduces a quick template based method to calibrate the human kinematic model purely based on inertial sensors. With the body attached orientation sensors to measure the orientation of limbs, and templates to confine the position of the distal limbs (feet and the hands), the dimension parameters in the human kinematic model can be determined based on the human body kinematics.

This method is time-saving and convenient. No additional external measurement devices are needed to measure the multiple body dimensions. The calibration results show that the dimension parameter errors can be controlled at the magnitude of one centimeter.

After the calibration of the human kinematic model, the human body kinematics is fully defined. The tracking of the human motion and interaction with the environment can be conducted after tracking the contact information. These will be

discussed in Chapter 5 and Chapter 6. Chapter 5 introduces the simultaneous localization and capture SLAC method for the tracking of motions with continuous contact interacts.

Chapter 5 Localization and Tracking: SLAC

The simultaneous localization and capture (SLAC) tracks the type of pHEI which have the following properties: 1). The contact interaction always exists. 2). The contact distal limbs should be stationary without sliding in the environment. In daily practice, pHEI in form of walking, climbing and dancing have continuous contact on the ground. The SLAC method can be applied in these scenarios. This chapter discusses on the SLAC methodology and the experimental results. The posture fine-tuning method to correctly represent the contact interaction will be discussed afterward.

Figure 5-1: Localization based on contacts and human kinematics

Figure 5-2: The working process of the localization method

In general, the contact interaction is illustrated in Figure 5-1. Here, we are interested in the contact position for localization purpose. The contact force is currently not tracked. The contact sensors are attached at the known locations of the body. Therefore, based on the human body kinematics, the relative displacement between the root point and the contact points (r_{ci} , with respect to the global frame) can be calculated using the forward kinematics of the body.

The process of the localization method is illustrated in Figure 5-2. During the initialization, the subject's absolute contact locations with respect to the environment are given. Then, the localization algorithm is applied to calculate the root location.

Let $p_{c1}, p_{c2} \dots$ denote the absolute location of the contact point in the environment, and $r_{c1}, r_{c2} \dots$ denote the displacement from the root to the contacting points. In case of a single contact point ($c1$), the root point location update is straight forward:

$$p_{0,c1} = p_{c1} - r_{c1} . \quad (5-1)$$

In multiple contact conditions, the root location can be calculated based on all the contact points. $(\mathbf{p}_{c1}, \mathbf{r}_{c1}), (\mathbf{p}_{c2}, \mathbf{r}_{c2}), \dots$. It is known from section 3.4 that the location uncertainty of the root point position can be calculated based on the kinematic uncertainty model. Let $\sigma_{x0,ci}, \sigma_{y0,ci}, \sigma_{z0,ci}$ denote the standard deviation of x, y and z coordinate of $\mathbf{p}_{0,ci}$. According to the probability analysis, the location of the root point can be calculated by

$$x_0 = \frac{\sum_{i=1}^n x_{0,ci} / \sigma_{x0,ci}^2}{\sum_{i=1}^n 1 / \sigma_{x0,ci}^2}, y_0 = \frac{\sum_{i=1}^n y_{0,ci} / \sigma_{x0,ci}^2}{\sum_{i=1}^n 1 / \sigma_{x0,ci}^2}, z_0 = \frac{\sum_{i=1}^n z_{0,ci} / \sigma_{x0,ci}^2}{\sum_{i=1}^n 1 / \sigma_{x0,ci}^2} \quad (5-2)$$

where $\mathbf{p}_{0,ci} = [x_{0,ci}, y_{0,ci}, z_{0,ci}]^T$ and $\mathbf{p}_0 = [x_0, y_0, z_0]^T$.

5.1 Localization with foot contacts

For daily activities, the feet contact with the ground. The location can be updated based on tracking the foot contacts. According to Section 3.3, during the right foot support phase, the location of the root can be updated from the right foot location $\mathbf{p}_{Rf}$ and the right leg kinematics:

$$\mathbf{r}_{Rf} = \sum_{i=1}^{n=4} {}^{CI}\mathbf{R}_{i-1} {}^{CI}\mathbf{l}_{i-1,i} \quad (5-3)$$

where $\mathbf{r}_{Rf}$ denotes the displacement between the root and the right foot with respect to the global frame. The location of the root can be calculated by

$$\mathbf{p}_{0,Rf} = \mathbf{p}_{Rf} - \mathbf{r}_{Rf} \quad (5-4)$$

During the Left foot support phase, the location of the root can be updated from left foot location $\mathbf{p}_{Lf}$ and the left leg kinematics:

$$\mathbf{r}_{Lf} = \sum_{i=1}^{n=4} {}^{C2}\mathbf{R}_{i-1} {}^{C2}\mathbf{l}_{i-1,i} \quad (5-5)$$

where $\mathbf{r}_{Lf}$ denotes the displacement between the root and the right foot with respect to the global frame. The location of the root can be calculated by

$$\mathbf{p}_{0,Lf} = \mathbf{p}_{Lf} - \mathbf{r}_{Lf} \quad (5-6)$$

In the multi-contact scenarios like the double support phase, the location of the root point can be up dated based on all the contact points and the whole body kinematics. To make it simple, the position of the root point is updated based on the average of the positions calculated from both feet during the double support phase.

When human moves, the contact points on the body parts changes with time. For example, the contact exchanges between the right and the left foot while walking. Therefore, in order to known the position of a new contact point, the tracked root position and the body kinematics are used to calculate the position of the new contact point. Given the tracked root location and the global displacement between the root and the new contact point $\mathbf{r}_{cj}$, the global location of the new contact point $\mathbf{c}_j$ can be calculated by

$$\mathbf{p}_{cj} = \mathbf{p}_0 + \mathbf{r}_{cj} \quad (5-7)$$

This new contact point can serve as a reference for localization purpose in the following time samples.

5.1.1 Contact Interaction Tracking

In order to detect the foot contact information on the ground, four force sensing resistors (FSR) with the controllers are fabricated under the insole of the shoes with known location on the foot.

Figure 5-3: The insole and the circuit diagram for FSR

Force Sensing Resistor (FSR) is a polymer thick film device which exhibits a decrease in resistance with an increase in the force applied to the active surface. Its force sensitivity is optimized for use in human touch control of electronic devices. For each FSR sensor, it forms a series circuit with a constant resistor (1K), as shown in Figure 5-3. The voltage of the connecting point is chosen as output. Thus, when contact happened, the contact condition of the foot can be detected through the increase of output voltage. The output is wirelessly sent to the laptop through Bluetooth module. If the output is larger than a threshold value, the sensor is considered as being contacted.

Alternatively, the IMU sensors mounted on the feet also can be used to detect the contact interactions. It is known that when the foot stands on the ground, the angular velocity and the acceleration of the foot is zero. Therefore, the measurement of the foot angular velocity and the acceleration can be combined together to detect the supporting phase of the foot. In cases when wearing the shoes is not applicable like playing the kendo and dancing, this contact detection method is useful.

5.2 SLAC Experiments

In order to validate the proposed method, and to study the accuracy of the system, the system is first benchmarked using the commercial optical motion capture system, Motion Analysis®. Then experiments were conducted to test on different ground conditions and different users. In SLAC Experiment, only the lower limb motions and the chest motion are tracked with eight IMU sensors and contact shoe pads. Six IMUs for the legs, one for the pelvis and one for the chest as introduced in Section 3.4.

The following scenarios are tested: mixtures of indoor/outdoor surroundings, stairs climbing, outdoor open air environments (uphill, downhill terrain the outdoor stairs). User tests (on for subjects) were also conducted to validate the adaptability of the system on different users.

Before the actual localization experiment, the kinematic model calibration of lower limb was conducted first for each participated subject. The human kinematic parameters are calculated for each subject. The localization and tracking are based on the calibrated kinematic model of each subject. Therefore, when mentioning “calibration” and “recalibration” in the tracking experiment, it means only calibration of the sensor position in the body frames, since the kinematic model of the subjects were already calibrated at the beginning of the experiment.

5.2.1 Benchmark Study with Motion Analysis®

The optical system Motion Analysis® is used as the benchmark system to provide the ground truth information during the localization. The system used in our benchmark study consists of eight cameras whose layout is illustrated in Figure 5-4.

In this benchmark study, the experiment protocol is as follows.

Figure 5-4: Layout of the eight camera Motion Analysis® system

Step 1: Individual subject wears the reflective markers and inertial system together as shown in Figure 5-5.

Step 2: The two systems are calibrated.

Step 3: The subject walks along the platform back and forth for four times at a normal speed. The walking motion is captured by the two systems at the same time.

In this study, the trajectories of the root point are the main concern. Therefore, the benchmarking experiment is to compare the trajectories of the root points captured from the two different systems. Thus, the root trajectories from the two systems are collected and compared after the trajectories are presented in the global coordinate frame.

An example of the two localization results along the walking direction are shown in Figure 5-6 for comparison. The red line provides the ground true reference from the optical system. The black line shows the result from the proposed method, and the blue line indicates difference between the two systems which represents the error of SLAC. The RMS of the error along all the sampled data is 0.20m with about 30m total distance travelled.

Figure 5-5: IMU and markers attachment for comparison

Figure 5-6: Localization results of the two systems

5.2.2 Indoor/ Outdoor Environment

To show the capability of the system applied to a large area in a mixture of indoor and outdoor environment, the tracking experiment is conducted inside and outside our laboratory (see Figure 5-7). The experiment procedures are as follows.

Figure 5-7: Indoor/Outdoor experiment

Step 1: After wearing the sensor system, the system is initialized and calibrated at the initial point shown in the left side of Figure 5-7.

Figure 5-8: Floor map of indoor environment and the corridor

Step 2: The subject walks around table C for three times as shown in Figure 5-8. While doing the experiment, the subject brings the laptop together with him.

Step 3: The subject walks around tables A and B for four times as shown in Figure 5-8.

Step 4: After that, the subject walks out of the laboratory and walks along the corridor. Finally, he returns back to the starting point.

The corridor is outdoor environment but is covered with a ceiling. This environment gives a good example of an environment not accessible by GPS. Therefore, wearable tracking system with proper localization accuracy can show advantage in such environments. In such even ground conditions, the altitude of the ground is used as a reference so that the incremental error along the Z-axis is prevented.

Table 5-1: Indoor/Outdoor loop experiments errors

Terrain	Close loop errors		Distance (m)
	X(m)	Y(m)	
Table A and Table B	0.048	0.086	32
	0.040	0.059	32
	0.064	0.083	32
	0.056	0.060	32
Table C	0.092	0.050	22
	0.063	0.072	22
	0.085	0.076	22
Corridor	0.655	-1.76	170

The localization trajectory of the root point is shown in Figure 5-8. The blue rectangles represent the floor maps of the tables and the room according to the dimensions of the layouts. The localization results for looping around the tables and corridors are listed in Table 5-1. Overall speaking, the error at the ending point for every single loop is one percent of the total distance travelled in looping around Table A and B, Table C and also the corridor of the laboratory. The localization result is shown to be repeatable.

5.2.3 Irregular Outdoor Terrains

5.2.3.1 Uphill and Downhill Slopes

For tracking the 3D position of a person, an experiment is conducted around an outdoor open air roundabout with shapes as shown in Figure 5-9. Note that the altitude of the ground varies, which shows a typical example of uneven uphill and downhill terrain. The experiment procedures are as follows.

Step 1: The subject stands in the starting position of the roundabout and calibrates the system as illustrated in Figure 5-9.

Step 2: Then, he starts to walk around the roundabout (clockwise) and goes back to its initial location. The subject brings the laptop together with him during the experiment in order to receive the sensor data.

Figure 5-9: Uneven terrain with uphill and downhill slopes

Step 3: He repeats **Step 2** one more time.

A computer regenerated location result based on the captured motion data including the location and the posture of the subject is shown in Figure 5-10. The X-axis, Y-axis and the starting point in Figure 5-9 and Figure 5-10 can be used to match their orientation for viewing.

It can be noticed that based on the proposed method, the ground profiles can be recovered based on the recorded localization data from the experiment area. In Figure 5-10, the upper edge of the pink surfaces indicates the detected ground surface during the experiment.

Because the measurement of the irregular terrain was not known in advance and is difficult to obtain, the localization error is presented by the distance between the starting point and the stopping point. The total distance for one round is estimated to be 98.6m. For each round, the position errors between the starting point and end point is within 0.7m along all the X-, Y-, Z- direction in such an outdoor environment.

Figure 5-10: Result of uphill and downhill slopes walk

5.2.3.2 Outdoor multi-orientation stairs

The multi-orientated stairs are commonly seen outside of the building in a hilly environment in NTU campus. The experiment of climbing a multi-orientation stair as shown in Figure 5-11 is conducted to demonstrate 3D localization. The subject in the figure is facing the south direction.

The experiment procedure is as follows.

Step 1: The subject stands at the ground level and calibrate the system.

Step 2: The subject climbs up the multi-oriented stairs to the top.

Step 3: The subject steps down the stairs and goes to the initial location.

Step 4: The subject repeats Step 2 and Step 3 twice.

Figure 5-11: Climbing outside stairs

Figure 5-12: Climbing up stairs

Figure 5-13: Step down stairs

The localization results and the lower limb motions are presented in Figures 5-12 and 5-13. The path length is about 65m. In the horizontal plane, the errors for the three rounds are $(-0.28, -0.60)\text{m}$, $(-0.32, -0.33)\text{m}$ and $(-0.22, -0.52)\text{m}$ in the North and East direction separately.

In the vertical direction, the standard height of each step is 180mm. This dimension is used to calculate the absolute vertical locations. Once a foot contact is detected, this coordinate of the foot along the Z-direction is set to be the same as the

coordinate of the standing stair. Therefore, there is no step missing in capturing the stair climbing.

5.2.4 User Tests

In order to validate that SLAC method is suitable for different persons, we need to test the system on different subjects. In the user test, we need to get proper places with known maps. Otherwise, we cannot visualize how well the person follows the maps. Therefore, the following user test experiments are conducted.

Firstly, localization of walking around a pond in NTU campus (as shown in Figure 5-14) is tested on four different subjects.

The total length for each round of walk is about 90m. The user data including the height and the body weight of the four subjects are listed in Table 5-2.

The human kinematic model (lower limbs) for each person is calibrated using the template-based calibration method described in Chapter 4. The experiment procedures for each person are as follows.

Table 5-2: User data

Item	Subject 1	Subject 2	Subject 3	Subject 4
Height (cm)	178	175	173	169
Weight (kg)	68	72	61.5	63

Figure 5-14: The pond for user tests

Step 1: The subject stands at the starting point, and calibrates the system

Step 2: The subject walks around the pond and returns back to the initial location

Step 3: The subject repeat **Step 2** twice.

Table 5-3: User test localization errors –Walking around the pond

Test	Subject 1 (m)	Subject 2 (m)	Subject 3 (m)	Subject 4 (m)
#1	(0.18, 0.31)	(0.05,0.81)	(0.61,0.58)	(0.33,0.88)
#2	(0.501, 1.01)	(-0.50,0.25)	(0.38, -1.26)	(0.25,0.75)
#3	(0.61, 0.47)	(0.30,1.03)	(0.52,1.25)	(0.17,1.32)
RMS Errors	(0.47, 0.67)	(0.34, 0.77)	(0.51,1.07)	(0.26, 1.01)

Figure 5-15: Localization results of all users walking around the pond.

For these four subjects, there are totally twelve root point trajectories. The localization results are shown in Figure 5-15. The green parallelogram indicates the outline of the pond. Other lines are the root trajectory of all users.

The RMS errors of the position of these twelve along the X-, Y- direction separately are listed in Table 5-3 . This ending position error is about one percent of the total path length.

Table 5-4: User test localization errors: Walking Straight Forward (10m)

	User1,#1	User1,#2	User1,#3	User2,#1	User2,#2	User2,#3
X(m)	-0.09	0.12	0.27	0.36	-0.16	-0.22
Y(m)	0.03	0.14	-0.05	0.03	0.07	0.00
	User3,#1	User3,#2	User3,#3	User4,#1	User4,#2	User4,#3
X(m)	-0.06	-0.19	-0.29	-0.15	0.33	0.25
Y(m)	-0.18	0.11	0.00	-0.25	-0.21	0.25

Figure 5-16: Localization results of all users walking around the lab corridor.

In order to test on the absolute accuracy in straight line traveling, we tested on walking straight forward for 10 meters on four subjects in an indoor environment. In the straightforward walking test, the localization error along the X- and Y- directions are shown in the following Table. The RMS Error for X is 0.227m, and 0.142m for Y.

Table 5-5: User test localization errors: Walking around the lab

	User1,#1	User1,#2	User1,#3	User2,#1	User2,#2	User2,#3
X(m)	0.20	-1.13	-1.47	0.50	1.63	-0.25
Y(m)	-0.40	0.60	-0.11	-1.73	1.81	-1.83
	User3,#1	User3,#2	User3,#3	User4,#1	User4,#2	User4,#3
X(m)	1.26	-0.56	1.12	-0.32	1.91	-1.60
Y(m)	0.20	-1.09	1.93	-1.94	0.97	-0.28

The localization of the corridor outside our lab is also tested for different users. In the walking around the RRC2 (53.6m by 16m) in the corridor outside. The localization results of the four users are shown in the Figure 5-16. The ending point errors are shown in Table 5-5. The RMS Error in X direction is 1.15m, and 1.29m in Y direction.

In all these user test experiments, results does not show obvious different between different users. Other than these experiments, many other testing experiments also shows that the localization results for different users are of the same range. The kinematic calibration eliminates the effects from different body sizes. Therefore, the system is applicable for different users.

5.3 Posture Fine Tuning

Figure 5-17: Demonstration of contact constraint correction

On one hand, contact interactions contribute in localization of human during the motion. On the other hand, in order to correctly represent the pHEI, kinematic constraints from the contact interactions need to be satisfied in the captured motion. Here, we also use the ladder climbing as an example. When the subject climbs the ladder as illustrated in Figure 5-17, his hands hold the ladder and the feet stand on the steps. The hands holding the ladder and the feet standing on the steps represents the contacts between the human body and the ladder. Such contacts become constraints between the human and the environment. Due to the redundant DOF in the human body, human can have internal movement without breaking these contacts.

From Section 3.3, it is known that once the location of the root point is calculated, the absolute positions of the distal limbs (feet and hands) on the body are directly available from the forward kinematics of the human body. Meanwhile, the actual positions of the contact points on the ladders are fixed. Then, the location errors of the contacting points (hands and feet) $\delta \mathbf{P}_n$ can be calculated by comparing the difference between the position of the distal limbs and the contacting positions on the ladder. The posture fine tuning is to re-adjust the parameters (the limb lengths and the limb orientations) inside the kinematic chains to eliminate these position errors on the distal limbs (see Figure 5-17 (1)). The properties of these parameters are important in the posture re-adjustment because the amounts of readjustment on the limb parameters are much dependent on their accuracy. For example, if the parameters of the thigh are more accurate than other limbs, the readjustment on it should be smaller. Thus, it is closely related to the kinematic uncertainty model of the human body as discussed in section 3.3.3.

5.3.1 Posture Fine Tuning Algorithm

In the ladder climbing example, there are multiple contact constraints to be satisfied. In this posture fine turning, the human skeleton should be considered as an integrated kinematic system instead of separate kinematic chains. Otherwise, *the*

symmetry of the skeleton model will be broken and the dimension of the limbs shared by two or more chains cannot be uniquely determined. Thus, in the posture fine tuning, the human body should be considered as one mechanism with all the distal limbs satisfying the kinematic constraints from the contacts. Thus, referring to Equation (3-18), we have

$$\mathbf{P}_A = \mathbf{B}_A \mathbf{X}_{all}, \quad (5-8)$$

where $\mathbf{P}_A = [\delta \mathbf{P}_{rh}^T, \delta \mathbf{P}_{lh}^T, \delta \mathbf{P}_{rf}^T, \delta \mathbf{P}_{lf}^T]^T \in \Re^{12 \times 1}$ is the vector representing the distal limb location errors (the hands and the feet with the subscript *rh*, *lh*, *rf*, *lf* denoting the chain of the right hand, the left hand, the right foot and the left foot respectively).

$\mathbf{X}_{all} \in \Re^{69 \times 1}$ is the column vector of the uncertain error parameters for all limbs as listed in Table A-1 in Appendix A.

$\mathbf{B}_A = [\mathbf{B}_{rh}^T, \mathbf{B}_{lh}^T, \mathbf{B}_{rf}^T, \mathbf{B}_{lf}^T]^T \in \Re^{12 \times 69}$ is the matrix that maps the uncertain parameters to the location errors of the distal limbs based on the forward kinematic of the human body.

For a healthy human subject, the skeleton model of the body can be symmetric on the right and the left sides. Therefore, the error parameters in the corresponding limb dimension on the right and left sides can be related as follows.

$$(\delta \mathbf{l}_{i-L,i})_R = \mathbf{S}(\delta \mathbf{l}_{i-L,i})_L, \text{ where } \mathbf{S} = \text{diag}(-1, 1, -1). \quad (5-9)$$

For example, the relationship between the dimension of the right thigh and the left thigh is

$${}^{c1} \delta \mathbf{l}_{1,2} = \mathbf{S} \cdot {}^{c2} \delta \mathbf{l}_{1,2} \quad (5-10)$$

The symmetric relationship of all the corresponding limbs in the kinematic model is defined based on the following equation,

$$\mathbf{0} = \mathbf{B}_S \mathbf{X}_{all} \quad (5-11)$$

where $\mathbf{B}_S \in \Re^{18 \times 69}$ is a constant matrix defining the symmetric relationship. Then, the constraint equations of the uncertain parameters become

$$\mathbf{P}_F = \mathbf{B}_F \mathbf{X}_{all}, \text{ where } \mathbf{P}_F = \begin{bmatrix} \mathbf{P}_A \\ \mathbf{0} \end{bmatrix}, \mathbf{B}_F = \begin{bmatrix} \mathbf{B}_A \\ \mathbf{B}_S \end{bmatrix}. \quad (5-12)$$

This constraint equation defines the relationship of the uncertain parameters. The model assumptions of the probability distribution of the angular errors $\delta\omega_i$, the $\delta l_{i-L,i}$ skeleton dimension errors as listed in Table A-1 in Appendix A will be used in calculating the value of the parameters for the posture fine tuning.

Based on the distribution of these error parameters, the optimal posture should be determined through finding the solution that maximize the probability density under the *constraint equations*: $\mathbf{P}_F = \mathbf{B}_F \mathbf{X}_{all}$. The probability density function of all the error parameters is,

$$P(\mathbf{X}_{all}) = \prod_{i=1}^m P(x_i), \quad (5-13)$$

where $\mathbf{X}_{all} = [x_1, x_2, \dots, x_{69}]^T$ are the limb dimension and orientation uncertainty parameters to be fine-tuned.

Based on the assumed uncertain model of the kinematic parameters as listed in Table A-1 in Appendix A, all the uncertain parameters (x_i) are normally distributed with a variance σ_{x_i} representing the uncertainty:

$$P(x_i) = \frac{1}{\sigma_{x_i} \sqrt{2\pi}} \exp\left(-\frac{x_i^2}{2\sigma_{x_i}^2}\right). \quad (5-14)$$

Thus, we have

$$P(\mathbf{X}_{all}) = \prod_{i=1}^m P(x_i) = C \cdot \exp\left(-\sum_{i=1}^m \frac{x_i^2}{2\sigma_{x_i}^2}\right), \quad (5-15)$$

where C is a constant defining the normalized coefficient.

The solution of $\mathbf{X}_{all}$ should be the values that maximize the probability $P(\mathbf{X}_{all})$ under the constraint equations from the human kinematic model: $\mathbf{P}_F = \mathbf{B}_F \mathbf{X}_{all}$. It means that the solution is most likely to be $\mathbf{X}_{all}$ among all the possible solutions. To get the solution, let

$$f = \sum_{i=1}^m \frac{x_i^2}{2\sigma_{x_i}^2}. \quad (5-16)$$

Then $P(\mathbf{X}_{all}) = C \cdot \exp(-f)$. Since $f > 0$ and $P(\mathbf{X}_{all}) = C \cdot \exp(-f)$ is monotonic decreasing function of f , the solution that maximize the probability $P(\mathbf{X}_{all})$ corresponds to the solution minimizing the following function f under the constraint equation: $\mathbf{P}_F = \mathbf{B}_F \mathbf{X}_{all}$.

For the minimization of f under the constraint equation $\mathbf{P}_F = \mathbf{B}_F \mathbf{X}_{all}$, the solution can be found using the Lagrange multiplier method [82]. The problem corresponds to finding the solution that minimize the following cost function g ,

$$g = f - \zeta(\mathbf{B}_F \mathbf{X}_{all} - \mathbf{P}_F). \quad (5-17)$$

where $\zeta \in \Re^{1 \times 30}$ is the row vector of all the Lagrange multipliers. The number of rows of $\mathbf{B}_F$ is 30. Since the minimum of the cost function g exist, the solution can be found where the partial derivatives of g with respect to $\mathbf{y} = [\mathbf{X}_{all}^T, \zeta^T]^T$ all become zero:

$$\frac{\partial \mathbf{g}}{\partial y_i} = 0, i = 1, 2, \dots, 99 \quad (5-18)$$

Then, we have the analytical solution,

$$\mathbf{y} = \begin{bmatrix} \lambda & -\mathbf{B}_F^T \\ \mathbf{B}_F & \mathbf{0} \end{bmatrix}^{-1} \begin{bmatrix} \mathbf{b}_r \\ \mathbf{P}_F \end{bmatrix} \quad (5-19)$$

where $\lambda_{i,j} = \frac{\partial}{\partial x_j} \left(\frac{\partial f}{\partial x_i} \right)$ which is actually diagonal matrix, and $\mathbf{b}_r$ is simply the right term.

In this way, all the parameters $\mathbf{X}_{all}$ are determined for the posture fine tuning.

When all the parameters are determined, the posture of the subject can be updated by eliminating the estimated errors. The orientation of the limb i is updated by

$$\mathbf{R}'_{\theta,i} = \delta \mathbf{R}_{\theta,i} \mathbf{R}_{\theta,i} = \text{rot}_z(\delta\theta_i(3)) \text{rot}_y(\delta\theta_i(2)) \text{rot}_x(\delta\theta_i(1)) \mathbf{R}_{\theta,i}. \quad (5-20)$$

where the functions $\text{rot}_z(\theta), \text{rot}_y(\theta), \text{rot}_x(\theta)$ calculate the rotation matrix of rotation about the Z-, Y-, X- axis with an angle θ . The calculation formulas can be found in [76]

The dimension of limbs is update by

$$\mathbf{l}_{i-L,i} = \mathbf{l}_{i-L,i} + \delta \mathbf{l}_{i-L,i}. \quad (5-21)$$

The linear approximations of the kinematic formulation are made during the position error presentation as shown in Equation (3-17). Therefore, the solution provided in Equation (5-19) is not the exact solution. There could be some minor remaining errors after one posture fine tuning. In this case, the posture fine tuning operates again to eliminate the slight errors. The overall process of the posture fine tuning is shown in Figure 5-18.

Figure 5-18: Working process of the posture fine tuning

The posture fine tuning repeats until the position errors of all the four distal limbs are sufficiently small ($\mathcal{E}$ is set to be 0.3cm in the experiment.)

5.3.2 Experiments of Posture Fine Tuning

To verify the posture refinement method, four fixed contact constraints are arranged in the environment to constrain the location of the feet and the hands. There locations are pre-defined with the measured dimensions as shown in Figure 5-19.

The experiment procedure of the posture fine tuning experiment is as follows.

Step 1. The subject wears the sensors, and calibrates the full body skeleton dimension model.

Step 2. He stands in front of the table and conducts the system calibration.

Step 3: The subject locates his feet and hands to match the constraint points. The footprints are used to constraint the location of the feet and the markers on the table are used to define the location of the wrists.

Figure 5-19. Layout of constraints

Step 4: The subject changes some postures while maintaining the contact positions as shown in Figure 5-20.

Figure 5-20. Movements with constraints

Figure 5-21: Postures before and after refinement (The grid unit is 0.5m)

The system tracks the motions of the subject based on the sensor measurement and the calibrated human kinematic model. The posture fine-tuning is conducted using the posture refinement method to meet the constraints from the contact interactions on the feet and the hands.

The captured postures and the postures after the fine tuning are shown in Figure 5-21. The black stars indicate the reference location of the constraint points. The multi-color models indicate the captured motions. The fine-tuned posture is presented as the red-color models. As shown in Figure 5-21, the contact interactions are satisfied after the posture fine tuning.

Note that this fine tuning is not the exact correction of the posture since the uncertainty model of the kinematic parameter errors (the limb length, the limb orientation etc.) is only an approximation rather than an exactly model. However, this uncertainty model works well to make the tracked motion correctly represent the contact interaction during the pHEI.

5.3.3 Tracking the pHEI via Wearable Sensors: A Summary

After introducing SLAC and the posture tuning, the working process of tracking the pHEI via wearable sensors is summarized by a state diagram as shown in Figure 5-22.

Step 1. Initially at state No. 1: Start, the subject put on all the sensors. Then, the location and posture of the human subject is initialized and the kinematic model of the human subject and the sensors are calibrated. Then, the system goes to state No. 2: **Kinematic model** (The kinematic model of the human and the sensor system are calibrated)

Step 2. The system captures the body movement so that the system goes to the state No.3 :**With Known Body Posture** (The human body posture are captured).

Step 3. The system detects the contact interaction so that the system goes to the state No.4: **Posture +Contacts** (Both the human body posture and the contacts are captured).

Step 4. Localization of the subject is conducted. The system goes to state No. 5: **Spatial Motion** (The human motion and his position with respect to the environment are captured).

Figure 5-22: working process of tracking the pHEI via wearable sensors

Step 5. The tracked posture is refined based on the contact interaction constraints. The state goes to State No. 6: *Spatial Motion + Interaction* (The human motion and interactions with the environment are captured)

Step 6. If the stop command is received, the system stops at State No. 7: Stop. Otherwise the system continues at **Step 2**, with the time updated.

5.4 Summary

This chapter discusses on the localization method SLAC for localization and motion tracking with continuous contact interactions. As the orientation sensors cannot directly measure the location of the person, SLAC makes it possible for the wearable system to track the location of the human during the pHEI without external infra-structures.

Experimental results show good accuracy in walking on even ground and irregular terrains, and stair climbing. Overall speaking, the accuracy of this system is within 1% to 2% of the total distance travelled. Compared with the existing localization techniques, this method does not depend on any external positioning devices. Since the laboratory systems are not applicable to large outdoor environments, this proposed method and further implementation can be very useful for applications such as outdoor sports, daily exercises and patient monitoring in houses.

With the introduced posture fine tuning in the tracking, the contact interaction during the pHEI can be correctly represented. For localization of human during motions with unstable contact states like jogging and jumping, this method is no longer available because there would be no contacts during the non-contact phases. Localization methods V-SLAC and A-SLAC for such kind of motions will be discussed in the next chapter.

Chapter 6 Localization and Tracking: V-SLAC and A-SLAC

The proposed SLAC method can track the position of the subject when there are continuous contacts with the environment. Challenges arise in the non-contact phases of some activities as there would be neither direct position measurement nor reference contact interactions to update the location of the person. However, if the 3D linear velocity of the root point of the person can be captured properly, the velocity integration over time can be applied to obtain the 3D position of the person in the short non-contact phase. Then, the spatial trajectory of the person can be continuously tracked in this manner. This is the fundamental idea of the velocity based SLAC (V-SLAC) and the acceleration based SLAC (A-SLAC) method, the two improved version of the SLAC for the change of environment contacts as illustrated in Figure 6-1, which corresponds to the state diagram Figure 5-22.

Figure 6-1: State diagram of different localization methods

6.1 Velocity Tracking

Theoretically, root point velocity estimation can be obtained by integrating the acceleration of the root point over a period of time. However, the slight projected acceleration errors [26] will lead to unbounded drifting errors in just a few seconds [84]. Thus, direct integration of the acceleration is not suitable for velocity tracking of daily applications.

It is possible to use some simplified model to estimate the walking velocity of human. In [85], a shank-mounted IMU is used to estimate the walking velocity based on an inverted pendulum model. The velocity estimation is only a scalar representing the velocity along the walking direction. This method is not accurate for different walking speeds. In personal localization study, researchers use the foot-mounted IMU sensors to track the foot velocities and position based on the zero velocity updates ZUPT algorithm [25, 26, 28, 33, 36]. The ZUPT method detects the stationary phase of the foot (shows up every 0.5 s for normal walking) during which the foot velocity is zero. This zero-velocity reference is used to correct the sensor measurement errors. The velocity and location errors are also corrected. ZUPTS method is useful for localization in regular walking. The foot velocity is also tracked while walking [26]. Note that the foot velocity is zero when it is supporting the body. Thus, the foot velocity cannot represent the actual velocity of the human subject.

In presenting the human velocity, the root point is close to the center of gravity of the whole body [86]. Therefore, the root point velocity is suitable to represent the velocity of the human subject. In SLAC, an IMU sensor is attached to the root point to measure the root acceleration. Inertial sensors can measure the angular velocity of the body limbs. Therefore, based on the velocity kinematic model of human body, the velocity of the root point can be estimated. This reference velocity can be combined with the integration of the root acceleration through a Kalman filter to obtain accurate and drift-free velocity value. Subsequently, the location of

the person can be tracked based on the time integration of this velocity update and kinematic calculations as discussed in SLAC. In this manner, the localization of the dynamic motions with non-contact phases such as jumping and jogging can also be realized [87, 88].

The pelvis IMU, which is attached to the root point, measures the root acceleration $\mathbf{a}_f$ (with gravity included) in the sensor frame. Thus, the root acceleration $\mathbf{a}_r$ with respect to the global reference can be obtained by transforming the accelerometer measurement from the body frame to the global frame, and eliminate the gravitational acceleration

$$\mathbf{a}_r = \mathbf{R}_{0S} \mathbf{a}_f - \mathbf{g}, \quad (6-1)$$

where $\mathbf{R}_{0S}$ denotes the measured orientation of the pelvis IMU.

Then, the root velocity $\mathbf{v}_k$ can be updated based on integration over time, with dt being the time interval:

$$\mathbf{v}_k = \mathbf{v}_{k-1} + dt \cdot \mathbf{a}_r. \quad (6-2)$$

Let $\delta \mathbf{R}_{0S}$ denotes the orientation error in the measurement and let $\delta \mathbf{a}_f$ denotes the white noise of the accelerometer measurement. Then, the error of the accelerations can be calculated by

$$\begin{aligned} \delta \mathbf{a}_r &= \delta \mathbf{R}_{0S} \mathbf{R}_{0S} (\mathbf{a}_f + \delta \mathbf{a}_f) - \mathbf{R}_{0S} \mathbf{a}_f \\ &\approx (\delta \mathbf{R}_{0S} - \mathbf{I}) \mathbf{R}_{0S} \mathbf{a}_f + \mathbf{R}_{0S} \delta \mathbf{a}_f, \\ &= \delta \mathbf{a} + \mathbf{R}_{0S} \delta \mathbf{a}_f \end{aligned} \quad (6-3)$$

where $\delta \mathbf{a} = \delta \hat{\xi}_0 \mathbf{R}_{0S} \mathbf{a}_f = -(\mathbf{R}_{0S} \mathbf{a}_f)^\wedge \delta \xi_0$, where $\delta \xi_0$ (3×1) denotes the corresponding angular vector of $\delta \mathbf{R}_{0S}$, $\delta \mathbf{R}_{0S} = e^{\delta \hat{\xi}_0} \approx \mathbf{I} + \delta \hat{\xi}_0$. Then, we know the property of the

acceleration noise which will be useful while combining the acceleration update with the velocity estimated from the velocity kinematics using a Kalman Filter.

6.1.1 Introduction to Kalman Filter

The Kalman filter addresses the general problem of trying to estimate the state $\mathbf{x} \in \Re^{n \times 1}$ of a discrete-time controlled process that is governed by the linear stochastic difference equation

$$\mathbf{x}_k = \mathbf{A}\mathbf{x}_{k-1} + \mathbf{B}\mathbf{u}_{k-1} + \mathbf{w}_{k-1}, \quad (6-4)$$

with a measurement $\mathbf{z} \in \Re^{m \times 1}$ that is

$$\mathbf{z}_k = \mathbf{H}\mathbf{x}_k + \mathbf{v}_k. \quad (6-5)$$

The random variables $\mathbf{w}_k$ and $\mathbf{v}_k$ represent the process and measurement noise respectively. They are assumed to be independent, white, and with normal probability distributions

$$p(\mathbf{w}) = N(0, \mathbf{Q}), \quad (6-6)$$

$$p(\mathbf{v}) = N(0, \mathbf{R}). \quad (6-7)$$

The process noise covariance $\mathbf{Q}$ and measurement noise covariance $\mathbf{R}$ matrices might change with each time step or measurement. $N(\bar{\mathbf{x}}, \sigma)$ represents the normal distribution function with $\bar{\mathbf{x}}$ denoting the average and σ denoting the standard deviation.

The $n \times n$ matrix $\mathbf{A}$ in the Equation (6-4) relates the state at the previous time step $k-1$ to the state at the current step k . The $n \times l$ matrix $\mathbf{B}$ relates the optional control input $\mathbf{u} \in \Re^{l \times 1}$ to the state $\mathbf{x}$. The $m \times n$ matrix $\mathbf{H}$ in the measurement Equation (6-5) relates the state to the measurement $\mathbf{z}_k$.

We define $\hat{\mathbf{x}}_k^- \in \mathfrak{R}^n$ to be a *a priori state estimate* at step k given knowledge of the process prior to step k , and $\hat{\mathbf{x}}_k \in \mathfrak{R}^n$ to be a *posteriori state estimate* at step k given measurement z_k . We can then define a priori and a posteriori estimate errors as $\mathbf{e}_k^- = \mathbf{x}_k - \hat{\mathbf{x}}_k^-$, and $\mathbf{e}_k = \mathbf{x}_k - \hat{\mathbf{x}}_k$.

The *priori estimate error covariance* is then

$$\mathbf{P}_k^- = E[\mathbf{e}_k^- \mathbf{e}_k^{-T}], \quad (6-8)$$

and the *posteriori estimate error covariance* is

$$\mathbf{P}_k = E[\mathbf{e}_k \mathbf{e}_k^T]. \quad (6-9)$$

The Kalman filter algorithm is as follows.

Discrete Kalman filter time update equations:

$$\hat{\mathbf{x}}_k^- = \mathbf{A}\hat{\mathbf{x}}_{k-1} + \mathbf{B}\mathbf{u}_{k-1} \quad (6-10)$$

$$\mathbf{P}_k^- = \mathbf{A}\mathbf{P}_{k-1}\mathbf{A}^T + \mathbf{Q} \quad (6-11)$$

Discrete Kalman filter measurements update equations:

$$\mathbf{K}_k = \mathbf{P}_k^- \mathbf{H}^T (\mathbf{H}\mathbf{P}_k^- \mathbf{H}^T + \mathbf{R})^{-1} \quad (6-12)$$

$$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_k^- + \mathbf{K}_k (z_k - \mathbf{H}\hat{\mathbf{x}}_k^-) \quad (6-13)$$

$$\mathbf{P}_k = (\mathbf{I} - \mathbf{K}_k \mathbf{H}) \mathbf{P}_k^- \quad (6-14)$$

The Kalman filter operates every sampling cycle to update the state variables $\hat{\mathbf{x}}_k$ based on the previous state value $\hat{\mathbf{x}}_{k-1}$ and the measurement z_k .

6.1.2 The Kalman Filter for Velocity Tracking

In the velocity update based on the integration of acceleration with time as shown in Equation (6-2), the discrete-time controlled process to estimate the state is governed by the following difference equation,

$$\mathbf{v}_k = \mathbf{A}_v \mathbf{v}_{k-1} + \mathbf{B}_v \mathbf{a}_{r,k-1} + \mathbf{W}_k \mathbf{w}_{k-1}, \quad (6-15)$$

where $\mathbf{v}_k$ denotes the velocity, $\mathbf{a}_{r,k-1}$ denotes the root acceleration and $\mathbf{w}_k$ denotes the white noise. Thus, according to Equations (6-2) and (6-3), we have:

Figure 6-2: IMUs attachment and using its measurements for velocity tracking

$$A_v = I_{3 \times 3},$$

$$B_v = \delta t \cdot I_{3 \times 3}$$

$$W_k = [-(R_{0S} a_f)^{\wedge}, R_{0S}] .$$

$$w = [\delta \xi_0^T, \delta a_f^T]^T$$

On the other hand, when a foot stationary phase is detected, the velocity of the root can be estimated from the kinematic chain of the supporting leg based on the velocity kinematics as discussed in Equation (3-13).

As shown in Figure 6-2, when the foot is stationary, the ankle velocity becomes zero. The root velocity can be calculated based on the motion of the shank, the thigh and the pelvis. Thus the measured velocity v_m based on velocity kinematics of the root is

$$v_m = -\sum_{i=0}^2 R_i (\omega_{i,b} \times l_{i,i+1}) . \quad (6-16)$$

For the existence of uncertainties in limb length and sensor measurements, the reference velocity from this kinematic calculation is represented as follows

$$v'_m = -\sum_{i=0}^2 \delta R_i \cdot R_i [(\omega_{i,b} + \delta \omega_{i,b}) \times (l_{i,i+1} + \delta l_{i,i+1})], \quad (6-17)$$

where δR_i denotes the orientation errors which corresponds to an angular error $\delta \theta_i$ and $\delta R_i = e^{\delta \hat{\theta}_i} \approx I + \delta \hat{\theta}_i$. The angular rate white noise is denoted by $\delta \omega_{i,b}$, and $\delta l_{i,i+1}$ denotes the uncertainty of the limb dimensions.

Referring to Equations (6-16) and (6-17), we have

$$\delta v_m = v'_m - v_m = V v_k . \quad (6-18)$$

where $V = [V_1, V_2, V_3]$, $v_k = [\delta\theta_1^T, \delta\omega_1^T, \delta l_{0,1}^T, \delta\theta_2^T, \delta\omega_2^T, \delta l_{1,2}^T, \delta\theta_3^T, \delta\omega_3^T, \delta l_{2,3}^T]^T$

and $V_i = -[(-R_i(\omega_{i,b} \times l_{i,i+1}))^\wedge, (-R_i l_{i,i+1})^\wedge \cdot R_i, (R_i \omega_{i,b})^\wedge \cdot R_i]$

According to Equation (6-18), we have the velocity measurement z_{vk} estimated from the limb kinematics as below:

$$z_{vk} = v_m = v'_m - Vv_k = H_v v_k + V_v v_k, \quad (6-19)$$

where $H_v = I_{3 \times 3}$,

and $V_v = -V$.

In this model, the accelerometer and gyroscope measurement errors are white noises as introduced in Section 0. The angular error and the skeleton dimension errors are approximated to be normally distributed as discussed in the kinematic uncertainty model described in Section 3.3. In this way, $p(w) = N(0, Q_w)$; $p(v) = N(0, R_v)$. Referring to the specification of the sensors in the Appendix B [72, 73] and the kinematic uncertainty model in Appendix A, the process noise covariance matrix of Q_w and R_v are determined.

Based on Equation (6-15) and (6-19), the velocity can be updated using the introduced Kalman Filter algorithm as shown in Figure 6-3 [89, 90].

In pHEI in forms of continuous contact phases like walking and climbing, the estimated velocity reference z_{vk} is always available. In dynamic motions like jogging and jumping with non-contact phases, the velocity reference is only available when the foot supports on the ground. In this situation, the velocity value of the root point comes from integrating the acceleration of the root point in the non-contact phases.

Figure 6-3: Velocity tracking Kalman filter

6.2 Velocity Based SLAC (V-SLAC)

In V-SLAC, during the contact phases, the location updated based on SLAC can be combined with the root velocity integration to update the subject's spatial location. The advantage of this data fusion is that the result obtained from SLAC governed by the body kinematics has no drift. Thus, a Kalman filter can combine these two location estimations together to provide accurate localization result. In the non-contact phases, the location is estimated by the integration of the velocity estimation over time. Figure 6-4 shows the working flow of the V-SLAC. The dashed-line in Figure 6-4 means that these references are only available during the contact phases.

Figure 6-4: Fusion algorithm for localization

Figure 6-5: Stride vector estimated from kinematics

In V-SALC, the stride vector is used as the state variables. The final location is calculated based on summing up all the stride vectors from the beginning to the end. Unlike walking where the steps are clearly defined based on the gait phases, the stride vector s_k in V-SLAC is defined in such a way that it starts from the beginning of a foot support phase, and ends at a new foot support phase showing up as illustrated in Figure 6-5.

In the root location update based on the integration of the root velocity over time, the discrete-time controlled process to estimate the state variable (s_k) is governed by the following difference equation.

$$s_k = A_s s_{k-1} + B_s v_{0,k-1} + w_{s,k-1} \quad (6-20)$$

$$s_k = A_s s_{k-1} + dt \cdot v_{0,k-1} + w_{s,k-1} \quad (6-21)$$

where $A_s = I_{3 \times 3}$, $B_s = dt \cdot I_{3 \times 3}$, and $w_{s,k}$ denotes the white process noise caused by the noise of the input velocity: $p(w_s) = N(0, Q_s)$. With the known error covariance matrix P_k of velocity input as shown in section 6.1, the process noise covariance in Equation (6-20) is $Q_{s,k} = \tau^2 P_k$.

On the other hand, the stride vector measurement is available based on the lower limb kinematics during the foot support phases (see Figure 6-5):

$$z_{s,k} = s_{m,k} + v_k^s, P(v_k^s) \sim N(0, R_{s,k}). \quad (6-22)$$

Where v_k^s denotes the measurement noise and the noise covariance is $R_{s,k}$ which can be calculated based on the kinematic uncertainty as introduced in Section 3.3. Then the stride vector can be combined based on Equation (6-21) and (6-22) using Kalman filter in Figure 6-6.

Figure 6-6: Localization Kalman filter in V-SLAC

After updating the step vector s_k , the root location can be calculated as follows.

$$p_0 = p_{0,s} + s_k, \quad (6-23)$$

where $p_{0,s}$ denotes the location of the root point at the starting moment of current step.

During the non-contact phase, only the left half of the Kalman filter is applied to update the stride vector value and also the covariance matrix $P_{s,k}$. In this manner, the spatial location of the human during both contact phases and non-contact phases can be captured continuously based on V-SLAC.

6.3 Experimental Validation of V-SLAC

To validate V-SLAC in velocity tracking and localization, a benchmark study of V-SLAC is first conducted based on the optical capture system Motion Analysis®.

The jumping motion experiment is conducted to test the system in tracking motions with non-contact phases.

6.3.1 Benchmark Study of V-SLAC

In the benchmark study of the V-SLAC method, the commercial optical motion capture system Motion Analysis® with eight cameras is used. The eight IMUs and shoe pad tracking system is used to validate V-SLAC method by a subject.

The experiment procedure is stated as follows.

Step 1: The subject wears the reflective markers along with the pHEI tracking system (IMU + shoe pad).

Step 2: The optical Motion Analysis system is calibrated.

Step 3: The wearable sensor system is calibrated.

Figure 6-7: Benchmark study of V-SLAC

Figure 6-8: Filtered velocity from Kalman filter

Step 4: The subject walks along the platform in the laboratory as shown in Figure 6-7 at the speed of about 1.2m/s. The motion is captured simultaneously by the two systems.

Step 5: The subject walks back and forth for six times.

In this benchmark experiment, the skeleton dimension parameters that are calibrated and saved for SLAC experiment is used for the kinematic calculation.

6.3.2 Velocity through V-SLAC

In the benchmark study, the reference velocity is achieved by differentiating the root marker position measured by the optical system. Figure 6-8 shows the result of V-SLAC and the reference velocity in all the X-, Y-, Z-axes directions after representing them with respect to the global frame. The reference velocity is shown

in red color whereas the velocity obtained from V-SLAC is shown in blue color. The RMS error along all the samples in the main walking direction (X-axis direction, along the platform as shown in Figure 6-7) is only 0.0048m/s for the entire 6 trials and it is within 0.5 % of the walking velocity. The RMS errors for the sideward (Y-axis) and Z-axis directions are 0.031m/s 0.018m/s respectively. In comparison with the main walking direction, the maximum errors along the sideward Y-axis and the vertical directions are larger; they are in the range of 2% to 3% of the walking velocity at 1.2m/s. The errors can be related to the skin deformation while moving. This method tracks the 3D velocity of the human using wearable sensors. The velocity accuracy can correctly represent the moving speed of the person in daily applications.

6.3.3 Localization through V-SLAC

The results of localization using V-SLAC for the benchmark study experiment are shown in Figure 6-9. In general, the average localization error is around 10 cm after walking back and forth for about every eight meters in all the six trials. The RMS error along all the samples for these six trials is 10.9 cm. This accuracy is at the same magnitude of SLAC method. For adults, 10 cm is less than one half of the foot length. This accuracy is sufficient for daily applications.

Figure 6-10 shows a tracking experiment for jumping in a room. In the jumping experiment, the subject wears the system and conduct the calibration. Subsequently, the subject jumps forward for two steps with a step length of about two meters.

The root point trajectory is chosen to presents the persons location. In this jumping motion description, the reference frame is defined as shown in Figure 6-10. Figures 6-11 and 6-12 show the trajectories of the captured positions, velocities and accelerations of the root point during the jumping motion along the vertical Z-axis and the front X-axis directions for two jumping steps.

Figure 6-9: Filtered localization result

Figure 6-13 shows the captured jumping motion based on V-SLAC. The arm motions are not captured in the eight - IMU configuration because there is no IMU on the arms.

Figure 6-10: Tracking experiment for jumping

Figure 6-11: Trajectory of root point in Z- direction

Figure 6-12: Trajectory of root point in X-direction

Figure 6-13: Captured jumping motions

With V-SLAC, motion tracking with wearable sensors is no longer restricted to activities with continuous ground contacts. For daily activities, motions with non-contact phases are quite common. Motions like joggings, continuous jumping, and hopping can also be tracked based on V-SLAC. Therefore, by adding V-SLAC tracking method to SLAC, wearable sensors have much broader applications for human activities.

6.4 SLAC with Acceleration Fine Tuning (A-SLAC)

In V-SLAC, the localization and tracking of motions with non-contact phases are realized after adding in the velocity. In many daily activities, such as walking and jogging, people may concern about the position and velocity of the human subject. The body parts movements are not of interests. Thus, it would be economical and convenient if the tracking system has as few sensors as possible.

In V-SLAC, IMU sensors are mounted on both legs so that the reference velocity from the body kinematics is available for contact phases of both feet. If we only

mount the sensor on one side of the legs to calculate the root velocity reference, the number of sensors can be reduced. The velocity of the root can be estimated based on the limb kinematics once the foot support phase of the leg with sensors show up. In this case, only three IMU sensors will be needed on the leg and the pelvis. For the non-contact phase of this leg, the velocity reference is not available. Therefore, the reference velocity comes in every other step. Because of data drift caused by the projected acceleration errors [26], direct integration of the root acceleration over time will not be able to provide accurate velocity value. However, if the acceleration errors can be estimated and eliminated, the acceleration value can be fine-tuned to avoid the velocity drift. Then it will be viable to use only three IMUs for velocity reference.

In order to measure the root velocity, the shank, the thigh and the pelvis motions need to be measured using IMUs. Therefore, three IMU sensors are required for measuring the lower limbs motions. This three-IMU localization and tracking method with acceleration fine tuning is called A-SLAC. In this section, we discuss the three IMU sensor configurations and the A-SLAC algorithm to track the velocity and position of the human. The APDM® IMU sensor is used in A-SLAC experiment because it has a larger acceleration measurement range as indicated in Appendix B.

6.4.1 Velocity Update and Acceleration Fine Tuning

The working principle of the acceleration fine tuning is illustrated in Figure 6-14. The pelvis IMU is mounted at the root point to measure the root point acceleration and the pelvis motion. When the foot (of the leg with sensors) stands on the ground, the velocity of the root point can be accurately tracked based on V-SLAC as discussed in Section 6.1. On the other hand, integration of the root point acceleration provides another velocity value that has the drifting errors. Comparing these two velocities can provide the drifting rate of the integrated velocity, which is the acceleration error.

Figure 6-14: Acceleration refinement algorithm

As illustrated in Figure 6-15, the true velocity of the root point is represented as a blue curve c_T . The velocity obtained from integrating the measured acceleration is plotted as a red curve c_I . The acceleration error is the drifting rate of the integrated velocity during this short period δT .

$$\delta a = \frac{v_t - v_{t,I}}{\delta T} \quad (6-24)$$

Figure 6-15: Velocity drifting illustration

Figure 6-16: Kinematic chain of lower limbs

It is reasonable to assume that during a very short period of time δt , the acceleration error does not change much. Thus, the acceleration error can be estimated by determining the drifting rate of the velocity in this short period of time.

Referring to Equation (6-15) and Figure 6-16, after fine tuning the root point acceleration, the discrete-time controlled process to estimate the velocity is governed by the following difference equation:

$$\begin{aligned} \mathbf{v}_k &= \mathbf{v}_{k-1} + (\mathbf{a}_{rm} - \delta \mathbf{a}) \cdot \delta t + (\delta t \cdot \mathbf{R}_r) \delta \mathbf{a}_f, \\ &= \mathbf{A}_A \mathbf{v}_{k-1} + \mathbf{B}_A \mathbf{u}_{k-1} + \mathbf{W}_A \mathbf{w}_{k-1} \end{aligned} \quad (6-25)$$

where $\mathbf{A}_A = \mathbf{I}_{3 \times 3}$,

$$\mathbf{B}_A = \delta t \cdot [\mathbf{I}_{3 \times 3}, \mathbf{I}_{3 \times 3}],$$

$$\mathbf{W}_A = \delta t \cdot \mathbf{R}_r,$$

$$\mathbf{u}_k = [\mathbf{a}_{r,m,k}^T, -\delta \mathbf{a}_{r,k}^T]^T.$$

$\mathbf{Q}_A$ represents the covariance of the white noise of the accelerometer measurement $\delta \mathbf{a}_f$.

Let the estimated root acceleration be $\mathbf{a}_{r,m} = \delta \mathbf{a}_r + \mathbf{a}_r$. The true acceleration is denoted by $\mathbf{a}_r$ and the acceleration error is $\delta \mathbf{a}_r$.

Then according to Figure 6-15, we have:

$$\int_{t-\delta T}^t \mathbf{a}_{r,m} dt = \int_{t-\delta T}^t (\delta \mathbf{a}_r + \mathbf{a}_r) dt = \delta \mathbf{a}_r \delta T + (\mathbf{v}_t - \mathbf{v}_{t-\delta T}). \text{ Thus}$$

$$\delta \mathbf{a}_r = \frac{\int_{t-\delta T}^t \mathbf{a}_{r,m} dt - (\mathbf{v}_t - \mathbf{v}_{t-\delta T})}{\delta T}. \quad (6-26)$$

In the discrete-time process, the acceleration error can be estimated in every n samples by

$$\delta \mathbf{a}_{r,k} = \frac{\sum_{i=k+1-n}^k \mathbf{a}_{r,m,i} dt - (\mathbf{v}_k - \mathbf{v}_{k+1-n})}{n dt}. \quad (6-27)$$

After the acceleration fine tuning as shown in Equation (6-25), the rest of the Equations in the Kalman filter for the velocity tracking are the same as V-SLAC discussed in Section 6.1. Subsequently, after the velocity is obtained, the position of the subject is updated in the same way as in V-SLAC.

Note that the velocity reference is only available for the leg with sensors during the foot contact. If the subject exercises the leg without sensors for a long time without letting the leg with sensors touching the ground, A-SLAC cannot work. This is one limitation of this method as compared with the SLAC and V-SLAC method. Also, the motion of the leg without sensors is also not tracked.

6.5 Experimental Validation of A-SLAC

6.5.1 Benchmark Study of A-SLAC

To validate the A-SLAC method in velocity tracking and localization, a benchmark study with the optical capture system Motion Analysis® is conducted for jumping and jogging motions. To test the A-SLAC accuracy in outdoor localization, an A-SLAC experiment is conducted around the outside of the laboratory.

In benchmark study of A-SLAC, the devices are: (1). The optical system Motion Analysis® with eight cameras. (2). Three IMU sensors and one pair of insole shoe pad. The experiment procedures are as follows.

Step 1: The subject wears the reflective markers along with three IMUs.

Step 2: The optical system is calibrated.

Step 3: The wearable IMU sensors is calibrated.

Step 4: The subject jumps forward and walks back to the initial location.

Step 5: The subject repeat **step 4** for five more times.

6.5.2 Velocity result in A-SLAC

The motions are captured by the wearable pHEI tracking system and the optical capture system simultaneously. The position of the marker attached at the root point serves as a reference of the human subject. The derivative of the position value with respect to time serves as a velocity reference to evaluate the velocity accuracy of A-SLAC. As the reference coordinates used by the two capture systems are different, a coordinate transformation between the two is needed to unify the data in order to compare in the same global frame [87]. In this benchmark study, it is required to define the reference frame following the geographical

direction (the X-axis is in the north direction, the Z-axis is in the upward direction. The Y-axis is defined according to the right-hand rule).

Figure 6-17 shows part of the result of the velocity from A-SLAC and the reference velocity in all directions. The reference velocity is represented as a dashed-line whereas the velocity from A-SLAC method is represented as a solid line

The RMS errors of the velocity along all directions are calculated from the RMS of the difference between the results from the two systems along all the time samplings. The RMS error in the main walking direction (Y-axis direction) is 0.051m/s, which is within 3 percent of the maximum velocity (1.5m/s). The RMS error for the vertical direction is 0.029m/s (about 2 % of the maximum velocity). In the lateral direction (blue), the result is less accurate (0.13m/s). The velocity accuracies in all (X-, Y-, Z-) directions are within 3% of the moving velocity for the walking and jumping motions.

Figure 6-17: Benchmark study of A-SLAC: root velocity (X: blue, Y: green, Z: red).

6.5.3 Localization result Using A-SLAC

Figure 6-18 shows the corresponding localization results in all X-, Y-, Z- directions (the unit is meter). The reference root position is represented as the dashed-line whereas the velocity from A-SLAC is represented as a solid line. In this experiment, the terrain is even ground. Therefore, in the Z-coordinate of the supporting foot is set to be the same as the ground during the localization. In this manner, the drifting error in the vertical direction is prevented.

The RMS error shows the difference between the captured location trajectory and the reference trajectory for all the sample time. The RMS error in the main walking direction Y-axis is 3.8cm (each trial is 3.6m in length). The RMS error for the vertical direction is 3.2cm. In the sideways (X) direction, the error is 5.7cm, about 2 percent of the trial length.

Figure 6-18: Benchmark study of A-SLAC: root position (X: blue, Y: green, Z: red).

6.5.4 Outdoor Experiment of A-SLAC

In order to test the system working for outdoor localization, the subject conducted an outdoor experiment around the room as shown in Figure 6-19. The experiment procedures are as follows.

Step 1: The subject wears the 3 IMUs + the Shoe Pad, and calibrates the system at the starting location as shown in Figure 6-19.

Step 2: The subject walks around the outside of a room (16m×53.6m) and goes back to the starting point.

Step 3: The subject repeats Step 2 for three more times.

The map of the room shown in Figure 6-19 provides a reference to evaluate the localization accuracy. The estimated traveled distance for one loop is about 170m. Figure 6-20 illustrates the root point 3D velocity and the trajectory of a sample path in the experiment while walking around the room. In the velocity (the first 50 second only, in order to show clearly) is plotted on the top.

Figure 6-19: Floor map for A-SLAC localization experiment

Figure 6-20: Outdoor localization and velocity tracking (X: blue, Y: green, Z: red)

For the four trials conducted, the position error after returning to the starting point are $(x, y) = (1.59, 0.91)$ m, $(1.08, 0.77)$ m, $(1.18, 1.09)$ m, $(0.95, 0.83)$ m. This is within 2 % of the total travelled distance. The absolute velocity error in this experiment is not available because there is no velocity reference in this experiment.

6.5.5 Jogging

In the jogging exercise, the velocity and the jogging distance are very important parameters to quantify the amount of exercise. A jogging experiment is conducted using this system. Firstly we measure a distance of 7.5 meter and mark the starting and ending position (this distance is short because the experiment is indoor since the power source is needed for the APDM sensor and receiver setup.). The jogging tracking experiment procedures are as follows.

Step 1: The subject calibrates the system in an initial starting position.

Step 2: The subject jogs for 7.5 meters at the speed of 2 to 3 m/s to the ending position and then jog back.

Step 3: The subject repeat Step 2 for three more times in the experiment.

The reference frame is defined as follows. The X-axis is in the north direction, the Z-axis is in the upward direction. The Y-axis is defined according to the right-hand rule. Figures 6-21 and 6-22 show the tracked velocity and location results (X-axis is in blue, Y-axis is in green, Z-axis is in red). The dashed-line denotes the results from integration of the root acceleration. The solid line denotes the results from A-SLAC method.

The tracked running distance matches nicely with the reference distance (7.5 m). The location error for each cycle is about 10cm with the total distance of 15 meter. From Figure 6-21 and Figure 6-22, it is clear that by eliminating the acceleration errors in A-SLAC, the drifting error of the velocity and the position is also significantly reduced. This jogging distance is still too short for evaluating the system in daily jogging exercise. Further study on longer distance outdoor jogging will be tested after solving the sensor data communication and power supply issues.

Figure 6-21: Jogging velocity

Figure 6-22: Jogging localization

6.6 Analysis

During the non-contact phase, the velocity is updated from the integration of the estimated acceleration. Therefore, the accuracy of the acceleration estimated from the IMU is very critical. In Equation (6-3), the acceleration errors are projected from the orientation errors. Thus, accurately tracking the orientation of the pelvis IMU is critical to improve the accuracy of this method.

Figure 6-23: Root accelerometer measurement while jumping

The acceleration during walking is much smaller compared with jumping and jogging. According to the system evaluation described in Chapter 7, the tracked orientation error of the IMUs during walking is about one degree. Thus, the acceleration error of the root point is very small (at the magnitude of $0.1m/s^2$ according to our measurements for the experiment). Therefore, once a new contact phase comes up in the V-SLAC and A-SLAC method, the velocity errors caused by this acceleration error can be corrected from the velocity reference.

In dynamic motions like running and jumping with no reference velocity during the non-contact phases, the velocity is updated from the integration of the estimated root acceleration. During the non-contact phases of jumping and running, the accelerometer measurement (a_f) of the root point is near to trivial. This is because the root point is very close to the center of gravity of the whole body experiencing a free fall during the non-contact phase. Figure 6-23 provides the a_f curve while jumping. It is noticeable in the figure that during the flight phase of jumping (around the time of 2s, 4s, 7s and 11s), the acceleration a_f becomes very small (the magnitude is less than $2m/s^2$). Hence the acceleration bias δa error is also close to zero according to Equation (6-3). As a result, the velocity update by integrating the root acceleration in the non-contact phases of is accurate.

6.7 Summary

In this chapter, velocity based simultaneous localization and capture V-SLAC and acceleration based simultaneous localization and capture A-SLAC are introduced. The V-SLAC method solves the problem of wearing inertial and contact sensors to track the activities with non-contact phases. V-SLAC first uses the velocity kinematics of the human body and the integration of root point acceleration to obtain the accurate root velocity of the human body. Then, the root velocity is applied to localize the subject during the non-contact phase. In this manner, tracking motions like jumping and jogging is possible.

In A-SLAC method, 3D velocity and location of the human are tracked using only three IMU sensors and a sensitive shoe pad system. The three IMU configurations significantly reduced the complexity of the wearable tracking system.

Table 6-1: Comparison of SLAC, V-SLAC and A-SLAC

Method	SLAC	V-SLAC	A-SLAC
Contacts	Always	Not all the time	Not all the time
Inputs for Localization	1. Human kinematics 2. Contacts	1. Human kinematics 2. Velocity kinematics 3. Contacts	1. Human kinematics 2. Velocity kinematics 3. Contacts 4. Fine-tuned root acceleration
No. of Sensors	8	8	3
Remarks			The right contact should appear every few seconds
Accuracy	Velocity: NA	Velocity: 1%-2%	Velocity: 3%
	Position: 1%-2%	Position: 1% - 2%	Position: 2%

The velocity and localization accuracy are evaluated and benchmarked with the commercial optical mocap system Motion Analysis®. Benchmark results show that the localization error of V-SLAC and A-SLAC are within 2 percent of the total

travelled distance. The velocity error is about one percent for V-SLAC, and is within 3 percent for A-SLAC. The characteristic of the methods-- SLAC, V-SLAC and A-SLAC are summarized in Table 6-1.

SLAC only uses the forward kinematics and the contact information for localization. Therefore, computational complexity of SLAC is minimal among the three methods. SLAC tracks the location as well as the motions of both legs, but it cannot track the root velocity of the subject. It also cannot capture the position of the subject during the non-contact phases of motions. V-SLAC uses the forward kinematics, velocity kinematics and the contact information for human velocity tracking and localization. This method is generally available for both contact phases and non-contact phases of motion. In V-SLAC, if the non-contact phase is more than two second, the tracking is not accurate (velocity errors $>0.2\text{m/s}$). The velocity, the position and the body motions are captured based on V-SLAC.

The A-SLAC method uses fewer sensors for the tracking then V-SLAC and SLAC. Therefore, the A-SLAC system has the least system complexity. The velocity and localization accuracy is not as good as V-SLAC, and A-SLAC cannot capture the motions of the legs without sensors. But when the accuracy is not very critical, A-SLAC with only 3 IMU systems can be very easily potable and convenient to use. After introducing the motion tracking and localization methods, the full-body motion and interaction tracking are introduced in next chapter.

Chapter 7 Full-body Motion Tracking and System Evaluation

7.1 Introduction

Lower limb activities contribute mostly to localization in the environment as described in Chapter 5 and Chapter 6. In many pHEI in the forms of daily activities such as the martial arts, sports, and dancing, the full body motion tracking is needed for learning purpose.

Figure 7-1: Gaits for the kendo practice

In some of these activities, additional gears are required. For example, golf clubs for golfing, tennis racket for playing tennis and wooden swords for practicing kendo. Tracking the movement of these hand-held gears along with human motion will be an important part of the pHEI to understand how humans perform in these activities. Hence, full-body motion tracking extended to external object handling and manipulation using wearable sensors based on SLAC, V-SLAC and A-SLAC is possible by incorporating the upper body motion tracking.

In this chapter, kendo is used as a simple example for full-body motion capture with external tool because kendo is a very structured sport and its range and speed of the movement are moderate compared with sports like table tennis and tennis. In kendo, the body moves with the feet standing on the ground in different gait patterns as shown in Figure 7-1. It has upper body, hand and tool movements as well as the lower limb motions while the subject brandishes the sword. Therefore, it is a good example for the full-body motion and interaction tracking.

Figure 7-2: Kendo

As shown in Figure 7-2, the subject practices kendo in an open space. Normally, the ground is flat for practicing Kendo. When practicing kendo, the subject holds the sword with both hands. The contact occurs between the feet and the ground as well as between the hands and the sword. The following key factors are very crucial for practicing kendo:

- (1). The movement of the body and the spatial trajectory of the root point of the subject.
- (2). The contact interaction between the subject and the environment.
- (3). The root velocity of the subject.
- (4). The position, orientation and the velocity of the sword.

Currently, the contacts between the hands and the sword are not monitored in real time. The contacting point on the kendo is stored in the computer at the beginning. Force sensors on the hands will be added to the hand to record the change contact conditions on the hands.

7.2 Kendo Tracking Experiments

In kendo practice, the subject has many types of gait patterns as shown in Figure 7-1. The speed of the lower body movement is low, usually less than 5m/s. The upper arms and the wooden sword movements are fast with high acceleration (based on the sensor measurements during our experimental study, the maximum acceleration is beyond the measurement range of the accelerometer-- 6G). The subjects practice on the gait patterns and brandishing the sword. In the experiment, three common kendo motions are chosen for tracking.

- (1): Step forward and backward (gait pattern are all *Ayumi-ashi*) while swinging the sword to the front to attack the opponent.
- (2): Step forward and prick the sword to the front to attack the opponent. Then, walk backward to return.
- (3): Step forward and swings the sword from the sideway to the front. Then, walk backward to return.

As illustrated in Figure 7-3, in the full-body pHEI tracking system, totally sixteen IMUs are used to fully track the motion of the subject. For the lower body motion, three IMUs are mounted on each leg, on the thigh, the shank and the foot respectively. Three IMUs are mounted on each arm, on the upper arm, forearm and the hand respectively. For the motion of the pelvis, the upper body, and the head, each has one IMU sensor to measure its motions. One sensor is attached to the sword just above the handle to measure the movements of the sword.

Figure 7-3: Full-Body pHEI tracking system

In kendo, the athletes do not wear shoes. Hence the shoe pad sensors cannot be used in this situation. The contact event is then detected based on tracking the support phase of the foot. As the gaits in kendo are relatively stable, the support phase of the foot can be easily captured based on the near- to- zero acceleration and angular velocity obtained by the foot IMU as introduced in Chapter 5.

The experiment procedures for kendo movement capture are:

Step 1: The subject puts on all the sensors and calibrates the kinematic model.

Step 2: The subject holds the sword horizontally with its arrow pointing to the front. Then, he calibrates all the sensors' positions on the body segments and the sword.

Figure 7-4: Tracking of kendo No.1

Step 3: The subject conducts motion (1) for three times.

Step 4: The subject conducts motion (2) for three times.

Step 5: The subject conducts motion (3) for three times.

7.3 Results of Kendo Motion Capture

The real-time tracking demonstration is available with the full-body and the sword motions. Photos of practicing Kendo are shown in Figures 7-4 to 7-6.

For the motion No. 1, the gait pattern and the body motions are clearly shown in the Figure 7-4. (1)-(3), the subject hold the sword on top of his head, and move forward. (4)-(5), the subject swing the sward to the front. (6). The subject steps back holding sword on top.

For the motion No. 2, as illustrated in Figure 7-5, the subject stabs the sword to the front for three times.

Figure 7-5: Tracking of kendo No. 2

Figure 7-6: Tracking of kendo No.3

For the motion No. 3, are illustrated in Figure 7-6. (1)-(2), the subject swings the sword from the front to the left side. (3)-(4). He swings the sword to the front. (5)-(6), he swings the sword to the front again. In the tracking of the three kendo motions,

- the full-body movements are captured;
- the location trajectory is tracked based on the localization methodology;

- the contact interaction are monitored based on the detection of the stationary phase of the feet;
- the velocity of the person is tracked based on the velocity tracking algorithm.

The position change of the captured motion of the subject in the screen can be seen based on the ground markers as shown in Figures 7-4 to 7-6.

In the full-body tracking, the sword accelerates and decelerates quickly with acceleration over the measurement range of the utilized IMU sensors ($> 6g$). The instantaneous speed of the sword can go higher than 20m/s. In such moments with high accelerations, the IMU orientation measurements are not accurate because the IMU tracking algorithm considers the measured acceleration as gravity for orientation reference [8, 9]. More advanced IMU tracking algorithm to track the fast motion of the sword is expected in the future.

7.4 System Evaluation

7.4.1 Localization Accuracy

Based on the indoor/ outdoor localization experiments mentioned in Section 5.2, the localization accuracy is generally within 1% to 2% of the total distance travelled. The accuracy of the system is sufficient in presenting the motion trajectory for daily practical applications. In pHEI tracking like the kendo and tai-chi, the position error is around 10 cm over a 10 meter motion range. Compared with the foot length of more than 20cm, this level of accuracy is good enough for practical motion tracking. For daily indoor and outdoor practices, we can recalibrate the subject's position when he goes back to the initial position to correct the location error.

7.4.2 Orientation Accuracy

The accuracy of the IMU orientation measurement is crucial in the kinematic measurement since other parameters need this orientation information to be transformed into the global frame f_w . According to the sensors specifications, the orientation error of the IMU sensor can be controlled within one degree for static measurements. However, the accuracy of the IMU tracking algorithm is sensitive to the acceleration of the measured object [9, 24]. In order to quantify the accuracy of the sensors, benchmark studies for the walking and jumping motion is conducted based on the optical system, Motion Analysis®. Three markers are directly mounted (rigid attachment) on each body-mounted IMU as shown in Figure 7-8.

The equipment for the benchmark study are: Motion Analysis®, eight IMUs mounted on the upper body (one IMU), the pelvis (one IMU) and the legs (six IMUs). The experiment procedures are as follows.

Figure 7-7: IMU and marker attachments for comparison

Figure 7-8: Attachment of markers on IMU

Step 1: The pHEI systems and the Markers are attached to the body, with the markers rigidly attached on each IMU as shown in Figure 7-7 and Figure 7-8.

Step 2: Calibrate the optical capture system and the pHEI system.

Step 3: The subject walks at the speed of about 1 m/s along the platform during which the motions are tracked by both optical capture system and the wearable IMU systems.

Step 4: The subject jumps along the platform and stands straight.

The orientation of the marker frames in the global frame is given by: $R_m = [x_m, y_m, z_m]$. Here, x_m, y_m, z_m represent the coordinate of X-, Y- and Z- axis of the marker frame in the global frame respectively. The marker frame is defined as shown in Figure 7-8. Through tracking the positions p_o, p_d, p_p of the marker O, D and P respectively, the orientation of this marker frame with respect to the reference frame can be calculated as follows.

$$\begin{aligned}
x_m &= \frac{p_D - p_O}{\|p_D - p_O\|} \\
y_m &= \frac{(p_D - p_O) \times (p_P - p_O)}{\|p_D - p_O\| \cdot \|p_P - p_O\|} \\
z_m &= x_m \times y_m
\end{aligned} \tag{7-1}$$

For comparison purpose, firstly a unique global reference frame should be used for both the optical capture system and the wearable IMU system. Secondly, one unique body frame should be chosen to present the sensor orientation so that the two orientation measured by both systems are represented in the same frame for comparison. Here the optical tracking system is used as the common reference frame for the benchmark study. The marker frame for each body sensor is chosen as the frame for sensor motion representation.

Let R_T denotes the orientation of the inertial reference frame with respect to the optical reference frame, and R_M denotes the relative orientation of the marker frame with respect to the IMU sensor frame as illustrated in Figure 7-8. The IMU orientation measurement outputs with respect to the IMU reference frame is denoted by R_i . Then the IMU orientation estimation presented in the optical reference frame is calculated by $R'_i = R_T R_i R_M$

Then the orientation outputs of both systems R_m and R'_i are presented in the same global reference frame. The orientation matrixes are transformed into the Z-Y-X Euler angles (or Yaw, Pitch, and Roll) for comparison.

From the calibration result of the optical motion capture system, we know that the marker location error is within 0.1mm after. The distances between the markers are more than 6 cm. The accuracy of the reference orientation is within the magnitude of 0.1 degree based on calculation (the small angle error that can generate 0.1mm error through 6cm: $0.1\text{mm} / 6\text{cm} \approx 0.0017\text{rad}$, about 0.1 degree).

Figure 7-9: Benchmark of IMU measurement: Right thigh

Table 7.1: Benchmark result of IMUs

Limbs	Correlation			RMS (deg)		
	Yaw	Pitch	Roll	Yaw	Pitch	Roll
Right Thigh	0.9744	0.9959	0.9421	1.6781	1.0172	1.4987
Right Shank	0.9465	0.9977	0.9407	1.0595	0.8272	1.3989
Pelvis	0.9501	0.9939	0.9655	0.9644	1.1126	1.4428

For walking, the results for the right thigh motion are shown in Figure 7-9. The red line represents the optical reference. The blue line represents the IMU result. The black line represents the error between them. As shown in Table 7.1, for the thigh, the shank and the pelvis motion measurement, the correlations of the corresponding angles (yaw, pitch and roll) between the two systems are higher than 0.94 and the RMS errors are less than 1.7 degree.

Figure 7-10: Comparison result for the trunk motion

Figure 7-11: Comparison result for the pelvis motion

Figure 7-12: Comparison result for the left shank motion

Table 7-2: RMS errors of sensors

Name	Yaw (deg)	Pitch (deg)	Roll (deg)
Trunk	0.7947	2.4527	0.2479
Pelvis	0.5951	2.3984	0.2330
Left Shank	0.7747	4.6557	1.5137
Left Thigh	1.0631	4.4703	0.8263
Left Foot	2.0416	5.6212	1.3136

For jumping motion, the comparison results for the trunk, the pelvis and the left shank are shown in Figure 7-10, Figure 7-11 and Figure 7-12 separately. The red line represents the optical reference, the blue line represents the IMU result, and the black line represents the error.

The RMS errors are calculated and listed in Table 7-2. The orientation estimation for jumping is generally less than five degrees. Compared with slow motion with one to two degrees in RMS errors, the measurement is less accurate for the dynamic behaviors. Such precision is still sufficient in posture measurement in practical applications as stated in [24].

7.5 Summary

This chapter discusses the full-body integration of the pHEI tracking system for daily practical applications. The kendo motion tracking shows the capability of the system in localization, velocity tracking, body movement and interactive contact tracking.

The system evaluation is also discussed. With one to two percent localization accuracy, one to five degree orientation accuracy and correct tracking of moving velocity and contact interactions, the system and methods can meet the requirements for daily practical applications.

Chapter 8 Conclusion

This dissertation systematically studies the system and methodologies on the tracking of pHEI via wearable inertial sensors and contact sensors. In order to represent the human body motion, the human kinematic model as well as the kinematic model of the body sensor system are properly formulated at the beginning. To determine the kinematic parameters of the human and the sensor kinematic model, a quick template-based calibration method is proposed. Based on the human body kinematic tracking, the contact interactions and the proposed motion tracking and the localization methods SLAC, V-SLAC and A-SLAC, the system is able to track the full-body motion interaction in daily pHEI such as walking, climbing, jumping and jogging. Experimental results show that the localization errors can be controlled within 1% to 2% of the total distance travelled. The velocity error can be maintained within 3% for both walking and jogging. The angular motions of the body segments can be captured in real-time with a sampling frequency from 20 to 100Hz. The orientation error is at about one degree for walking, climbing, and three to degrees for jumping and jogging.

After developing the motion interaction tracking and the localization methods, a wearable full-body motion and interaction pHEI tracking system is developed. In the representation of the full-body motion tracking with the hand-held gear, the kendo practice is chosen as an example. The tracking results show that the full-body motion, the motion of the hand-held sword and the contact interaction between the human and the environment can be correctly captured online. The gait patterns, the location trajectory of the human subject as well as the body velocity are fully monitored.

In this dissertation, the proposed self-contained pHEI tracking system provides an economical and convenient solution for the tracking of daily pHEI activities. Compared with the integration of laboratory-based force platform and the optical

motion tracking system, this system is easily available for daily applications in various environments. The system initialization and calibration are easy and time-saving. The tracking applications can be conducted anywhere as long as a data capturing and computing device and the pHEI tracking system are available at hand.

One of the major achievements for the wearable sensor based motion interaction tracking system is that the proposed V-SLAC and A-SLAC methods solve the accurate localization problem for motions with non-contact phases. Since the non-contact phases are quite common for daily activities including jumping and running features, V-SLAC and A-SLAC largely broadens the application range of using wearable inertial and force sensors for pHEI tracking.

8.1 Contributions

1. A fast template-based human kinematic model calibration method.

In this dissertation, a fast template-based human kinematic model calibration method based on the wearable IMU sensor system is introduced. Based on the analysis of the kinematics and the calibration model of the human body, the method calibrates the human limb dimensions simply by matching a set of pre-designed footprint and hand mark templates. The calibration procedure only needs a few minutes to determine the dimensional parameters of the body limbs.

The proposed calibration method does not depend on any external device to measure the limb dimensions. Therefore, the preparation time of the system is significantly shortened. The costs for measurement devices like anthropometry frame are also saved.

2. Velocity tracking and localization

Based on the calibrated human kinematic model, tracking the contact interaction and the human body kinematic tracking, a method called simultaneous localization

and capture SLAC is proposed. The self-contained method does not depend on any infra-structures for human motion tracking and 3D localization. The localization and tracking are implementable for both even and uneven terrain conditions for different users. Experimental validations of the indoor / outdoor even ground, stairs, and uphill/ downhill slopes showed that the localization error can be controlled within 1% to 2% of the total distance travelled.

During non-contact phases, the absence of absolute location measurement and contacts with the environment makes the positioning of the human subject a challenge for the self-contained wearable tracking system. In existing discussion on the localization methods, localization method for such motions with non-contact phases is lacking for the wearable inertial system. This dissertation proposed a real-time velocity based SLAC method (V-SLAC) based on the body kinematics and the interactive contacts. The body velocity of the subject during various motions can be tracked in-real time. After implementing the velocity tracking function to the system, the velocity data and the lower limb kinematics can be combined to continuously track the spatial location of the subject during both the contact and the non-contact phases. This contributes in the tracking of dynamic motions with non-contact phases.

In daily applications, motions like jumping, jogging all have non-contact phases. With this tracking function, the system can be used to track daily physical activities for various types of slow and dynamic motions in both indoor and outdoor environments.

With the SLAC and V-SLAC, the IMU sensors are no longer restricted to body posture tracking. The spatial position and motion of the human body can be correctly tracked without volume limitations. This makes the inertial sensor based system viable for broader applications in large area and different terrain conditions.

In the applications where the velocity and location of a subject are the only concerns, not the body movement, A-SLAC is proposed using three IMU sensors for 3D velocity tracking and localization. The three IMU tracking system can be used to deal with localization and velocity tracking issues for various motion patterns such as walking, jumping and jogging. With only three IMU sensors, the system complexity and the cost are much reduced.

3. The full body motion, interaction tracking via wearable inertial and contact sensors.

The full-body motion and interaction tracking is realized using the wearable IMU and force sensor system. The laboratory-based systems can only capture the motion of human in small capture volume. Existing solely wearable systems also have not shown scientific results in motion tracking and localization in large capture range. In this dissertation, the motion tracking and 3D localization on the large scale uneven terrains and multi-oriented stairs are conducted. The 3D human motion profiles while interacting with the environment are accurately captured.

Also, in order to correctly represent the full-body motion interaction with the environment such as the hands and feet contacting the environments, the posture fine tuning method is introduced to correctly represent the contact interaction with the environment. Then, the full-body motion and correct contact interaction tracking is realized.

8.2 Future Work

The system is now available for various full-body motion interactions in different terrain conditions. However, there are still limitations.

Firstly, the localization error is proportional to the distance travelled. Therefore, after a long journey, one kilometer for example, the localization error could be more than 10 meters. If external localization signal like GPS is combined together, this problem will be solved.

Secondly, the skin and muscle movements will introduce errors in the limb motion measurement. With proper sensor mounting, these will not affect much for normal motions like walking, climbing, dancing etc. But the skin and muscle movements will increase especially for high dynamic motions like triple jump and the 100 meter race. This is a common problem for all types of motion tracking devices, not only for this wearable sensor system.

Also, the disturbance in the magnetic field distribution from the ferromagnetic substance in the environment will lead to the heading errors in the IMU sensor measurements. This will also affect the motion tracking and localization accuracies. Researchers have already put efforts into this issue [9]. To solve this issue, more robust IMU tracking algorithms to deal with this magnetic disturbance is required in the future.

In fast and high dynamic motion tracking, the physical quantities such as the angular velocities, acceleration and velocity significantly increase. Therefore, in such motion scenarios, there are many technical difficulties to overcome. For example, in kendo, the fast motion of the sword is not captured accurately in real-time. As the motion becomes faster, the inertial sensor's orientation tracking accuracy will decrease due to the limitations in the existing tracking algorithm [23, 24]. In order to make the tracking sensors more robust for dynamic motion tracking, the sensor's tracking algorithm need to be improved to accurately capture high dynamic motions. This is very useful for sports related applications.

The kinetic tracking issues during the human-environment interaction have not been implemented into the tracking system. Further research works can be

conducted on the tracking methodology for the kinetic quantities such as environment reaction forces, the body joint reaction forces, the joint torques and the muscle strengths. Eventually, the pHEI tracking with full kinematic and kinetic tracking capabilities using wearable sensor systems can be expected.

The current existing function in motion tracking, localization, velocity tracking, full-body motion and interaction tracking can provide many useful motion data for various applications. Applications in exercises, sports, biomechanics (diagnose, rehabilitation etc.), entertainments and animation can be realized based on the current system and further development of the tracking systems and methodologies.

Appendix A

Based on the accuracy of the estimation in orientation and limb dimensions, the orientation error of the limbs are presented in the form of yaw, pitch and roll angles (Z-Y-X Euler angle), the standard derivations of the angular errors are all approximately set to be 0.035rad (2 degree) for all the three angles. The limb vector error is presented with errors along the X-, Y-, and Z- axis. The standard derivations of the limb vectors are all set to be 0.015m. For special joints like the shoulder and waist, we set the standard derivations to be 3cm. Please note that, this is only a simplified model, especially for upper body. The actual uncertainty model with precise distribution of the error parameters is outside the scope of this dissertation.

Table A-1: Approximate probability distribution of the uncertain parameters in human kinematics

Items	Orientation Error Distribution (YPR, in rad)	δl Distribution
Pelvis	Norm(0, 0.035); Norm(0, 0.035); Norm(0, 0.035)	Right Hip Norm (0,0.015m); Norm (0,0.015m); Norm (0,0.015m)
		Left Hip Norm (0,0.015m); Norm (0,0.015m); Norm (0,0.015m)
		Waist Norm (0,0.015m); Norm (0,0.015m); Norm (0,0.03m)
Right Thigh	Norm(0, 0.035); Norm(0, 0.035); Norm(0, 0.035)	Norm (0,0.015m); Norm (0,0.015m); Norm (0,0.015m)
Right Shank	Norm(0, 0.035); Norm(0, 0.035); Norm(0, 0.035)	Norm (0,0.015m); Norm (0,0.015m); Norm (0,0.015m)
Left Thigh	Norm(0, 0.035); Norm(0, 0.035); Norm(0, 0.035)	Norm (0,0.015m); Norm (0,0.015m); Norm (0,0.015m)
Left Shank	Norm(0, 0.035);	Norm (0,0.015m);

	Norm(0, 0.035); Norm(0, 0.035)	Norm (0,0.015m); Norm (0,0.015m)
Trunk	Norm(0, 0.035); Norm(0, 0.035); Norm(0, 0.035)	Right Shoulder Norm (0,0.03m); Norm (0,0.015m); Norm (0,0.03m)
		Left Shoulder Norm (0,0.03m); Norm (0,0.015m); Norm (0,0.03m)
		Neck Norm (0,0.015m); Norm (0,0.015m); Norm (0,0.03m)
Right Forearm	Norm(0, 0.035); Norm(0, 0.035); Norm(0, 0.035)	Norm (0,0.015m); Norm (0,0.015m); Norm (0,0.015m)
Right Upper arm	Norm(0, 0.035); Norm(0, 0.035); Norm(0, 0.035)	Norm (0,0.015m); Norm (0,0.015m); Norm (0,0.015m)
Left Forearm	Norm(0, 0.035); Norm(0, 0.035); Norm(0, 0.035)	Norm (0,0.015m); Norm (0,0.015m); Norm (0,0.015m)
Left Upper arm	Norm(0, 0.035); Norm(0, 0.035); Norm(0, 0.035)	Norm (0,0.015m); Norm (0,0.015m); Norm (0,0.015m)

Appendix B

The specifications of the two types of sensors are listed in Table B-1, Table B-2.

Table B-1: Specifications of the K-Health IMUs

Name	Parameters
Output	Euler angle, acceleration ,angular velocity
Communication	Wireless
Maximum Angular Rate	1200 degree/s
Sampling Rate	100Hz
Effective Range	30m
Accuracy	Yaw: 1 ° ,Pitch and Roll: 0.4 °

Table B-2: Specifications of the APDM IMUs

Item	Accelerometer	Gyroscope	Magnetometer
Axes	3 axes	3 axes	3 axes
Range	± 6g	± 2000 deg/s	± 6 Gauss
Noise	0.0012 m/s ² /√Hz	0.05 deg/s/√Hz	0.5 mGauss/√Hz
Sampling Rate	20 to 128 Hz	20 to 128 Hz	20 to 128 Hz

References

- [1] R. Wasinger and W. Wahlster, "Multi-modal human–environment interaction," in *True Visions*, ed: Springer Berlin Heidelberg, 2006, pp. 291-306.
- [2] E. BLOOD, T. STEINER, and H. JONES, "Magnetic position and orientation tracking system," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 15, no. 5, pp. 709-718, 1979.
- [3] T. Molet, R. Boulic, and D. Thalmann, "A real time anatomical converter for human motion capture," in *Proceedings of 7th Eurographics International Workshop on Animation and Simulation*, Poitiers, France, 1996, pp. 79-89.
- [4] G. K. Cheung, S. Baker, J. Hodgins, and T. Kanade, "Markerless human motion transfer," in *Proceedings of 2nd International Symposium on 3D Data Processing, Visualization and Transmission*, Thessaloniki, Greece, 2004, pp. 373-378.
- [5] T. Shiratori, H. S. Park, L. Sigal, Y. Sheikh, and J. K. Hodgins, "Motion capture from body-mounted cameras," *ACM Transactions on Graphics (TOG)*, vol. 30, no. 4, pp. 31-38, 2011.
- [6] MetaMotion. (2013). <http://www.metamotion.com>.
- [7] D. Vlasic, R. Adelsberger, G. Vannucci, J. Barnwell, M. Gross, W. Matusik, *et al.*, "Practical motion capture in everyday surroundings," *ACM Transactions on Graphics (TOG)*, vol. 26, no. 3, pp. 35-44, 2007.
- [8] E. Bachmann, "Inertial and magnetic tracking of limb segment orientation for inserting humans into synthetic environments.," PhD Thesis, Naval Postgraduate School Monterey CA., Naval Postgraduate School, Monterey, California, 2000.
- [9] D. Roetenberg, "Inertial and magnetic sensing of human motion," PhD Thesis, Universiteit Twente, 2006.
- [10] D. Roetenberg, H. Luinge, and P. Slycke, "Xsens MVN: full 6DOF human motion tracking using miniature inertial sensors," Xsens Technologies, 2009.
- [11] C. Frigo, M. Rabuffetti, D. Kerrigan, L. Deming, and A. Pedotti, "Functionally oriented and clinically feasible quantitative gait analysis

- method," *Medical and Biological Engineering and Computing*, vol. 36, no. 2, pp. 179-185, 1998.
- [12] Y. Fujimori, Y. Ohmura, T. Harada, and Y. Kuniyoshi, "Wearable motion capture suit with full-body tactile sensors," in *Proceedings of IEEE International Conference on Robotics and Automation.*, Kobe, 2009, pp. 3186-3193.
 - [13] *The Gait Cycle.* (2013). <http://physicaltherapy.about.com/od/abbreviationsandterms/a/Gaitcycle.htm>.
 - [14] R. Tolley and R. S. Tolley, *Sustainable transport: planning for walking and cycling in urban environments*: CRC Press, 2003.
 - [15] *Running Gait.* (2013). http://www.corerunning.com/running_gait.html.
 - [16] J. F. Fixx, *The complete book of running*: Random House, New York, 1977.
 - [17] P. Hackney, S. Manno, and M. Topaz, *Study guide for elementary Labanotation*: Dance Notation Bureau Press, 1977.
 - [18] T. D. Roberts, *Understanding balance: the mechanics of posture and locomotion*: Nelson Thornes, 1995.
 - [19] T. D. M. Roberts, *Understanding balance: the mechanics of posture and locomotion*: Singular Publishing Group, 1995.
 - [20] C. Fischer, K. Muthukrishnan, M. Hazas, and H. Gellersen, "Ultrasound-aided pedestrian dead reckoning for indoor navigation," in *Proceedings of the first ACM international workshop on Mobile entity localization and tracking in GPS-less environments*, New York, USA 2008, pp. 31-36.
 - [21] L. Ojeda and J. Borenstein, "Non-GPS navigation for security personnel and first responders," *Journal of Navigation*, vol. 60, no. 3, pp. 391-400, 2007.
 - [22] S. Beauregard, "Omnidirectional Pedestrian Navigation for First Responders," in *Proceeding of 4th Workshop on Positioning, Navigation and Communication*, Hannover, 2007, pp. 33-36.
 - [23] M. Brodie, A. Walmsley, and W. Page, "Fusion motion capture: a prototype system using inertial measurement units and GPS for the biomechanical analysis of ski racing," *Sports Technology*, vol. 1, no. 1, pp. 17-28, 2008.

- [24] M. A. D. Brodie, "Development of fusion motion capture for optimization of performance in alpine ski racing," PhD Thesis, Massey University, Massey University, 2009.
- [25] E. Foxlin and S. Wan, "Improved pedestrian navigation based on drift-reduced MEMS IMU chip," in *Proceedings of the 2010 ION International Technical Meeting*, San Diego, CA 2010, pp. 220-229.
- [26] E. Foxlin, "Pedestrian tracking with shoe-mounted inertial sensors," *IEEE Computer Graphics and Applications*, vol. 25, no. 6, pp. 38-46, 2005.
- [27] O. Bebek, M. A. Suster, S. Rajgopal, M. J. Fu, H. Xuemei, x, *et al.*, "Personal Navigation via High-Resolution Gait-Corrected Inertial Measurement Units," *IEEE Transactions on Instrumentation and Measurement*, vol. 59, no. 11, pp. 3018-3027, 2010.
- [28] M. Kourogi and T. Kurata, "Personal positioning based on walking locomotion analysis with self-contained sensors and a wearable camera," in *Proceedings of the 2nd IEEE/ACM International Symposium on Mixed and Augmented Reality*, Washington, DC, USA, 2003, pp. 103-112.
- [29] J. Torres-Solis, T. Falk, and T. Chau, "A review of indoor localization technologies: towards navigational assistance for topographical disorientation," *Ambient Intelligence. InTech, Vukovar, Croatia* pp. 51-84, 2009.
- [30] Y. Gu, A. Lo, and I. Niemegeers, "A survey of indoor positioning systems for wireless personal networks," *IEEE Communications Surveys & Tutorials*, vol. 11, no. 1, pp. 13-32, 2009.
- [31] J. Hesch, F. Mirzaei, G. Mariottini, and S. Roumeliotis, "A Laser-Aided Inertial Navigation System (L-INS) for human localization in unknown indoor environments," in *IEEE International Conference on Robotics and Automation*, Anchorage, AK, 2010, pp. 5376-5382.
- [32] M. Kourogi, N. Sakata, T. Okuma, and T. Kurata, "Indoor/outdoor pedestrian navigation with an embedded gps/rfid/self-contained sensor system," *Advances in Artificial Reality and Tele-Existence*, pp. 1310-1321, 2006.
- [33] G. Lachapelle, S. Godha, and M. Cannon, "Performance of integrated HSGPS-IMU technology for pedestrian navigation under signal masking," in *Proceedings of European Navigation Conference*, Manchester, UK, 2006, pp. 8-10.

- [34] V. Renaudin, O. Yalak, P. Tomé, and B. Merminod, "Indoor navigation of emergency agents," *European Journal of Navigation*, vol. 5, no. 3, pp. 36-45, 2007.
- [35] O. Woodman and R. Harle, "Pedestrian localisation for indoor environments," in *Proceedings of the 10th international conference on Ubiquitous computing*, Seoul, Korea, 2008, pp. 114-123.
- [36] L. Ojeda and J. Borenstein, "Non-GPS navigation with the personal dead-reckoning system," *Unmanned Systems Technology IX*, vol. 1, pp. 6561-6571, 2007.
- [37] K. Jonghyuk and S. Sukkarieh, "Improving the real-time efficiency of inertial SLAM and understanding its observability," in *proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2004, pp. 21-26.
- [38] J. Kim and S. Sukkarieh, "Real-time implementation of airborne inertial-SLAM," *Robotics and Autonomous Systems*, vol. 55, no. 1, pp. 62-71, 2007.
- [39] M. Baglietto, A. Sgorbissa, D. Verda, and R. Zaccaria, "Human navigation and mapping with a 6DOF IMU and a laser scanner," *Robotics and Autonomous Systems*, vol. 59, no. 12, pp. 1060-1069, 2011.
- [40] J. Folkesson, P. Jensfelt, and H. I. Christensen, "Vision SLAM in the Measurement Subspace," in *Proceedings of IEEE International Conference on Robotics and Automation*, Barcelona, Spain, 2005, pp. 30-35.
- [41] A. J. Davison, Y. G. Cid, and N. Kita, "Real-time 3D SLAM with wide-angle vision," in *Proceedings of IFAC Symposium on Intelligent Autonomous Vehicles*, Lisbon Portugal, 2004, pp. 205-219.
- [42] C. Goodvin, E. Park, K. Huang, and K. Sakaki, "Development of a real-time three-dimensional spinal motion measurement system for clinical practice," *Medical and Biological Engineering and Computing*, vol. 44, no. 12, pp. 1061-1075, 2006.
- [43] J. Favre, B. Jolles, R. Aissaoui, and K. Aminian, "Ambulatory measurement of 3D knee joint angle," *Journal of biomechanics*, vol. 41, no. 5, pp. 1029-1035, 2008.
- [44] M. Lafortune, P. Cavanagh, H. Sommer III, and A. Kalenak, "Three-dimensional kinematics of the human knee during walking," *Journal of biomechanics*, vol. 25, no. 4, pp. 347-357, 1992.

- [45] H. Luinge, P. Veltink, and C. Baten, "Ambulatory measurement of arm orientation," *Journal of biomechanics*, vol. 40, no. 1, pp. 78-85, 2007.
- [46] K. Nguyen, I. Chen, Z. Luo, S. Yeo, and H. Duh, "A wearable sensing system for tracking and monitoring of functional arm movement," *Mechatronics, IEEE/ASME Transactions on*, vol. 16, no. 2, pp. 213-220, 2009.
- [47] Y. Tao, H. Hu, and H. Zhou, "Integration of vision and inertial sensors for 3D arm motion tracking in home-based rehabilitation," *The International Journal of Robotics Research*, vol. 26, no. 6, pp. 607-615, 2007.
- [48] N. Miller, O. C. Jenkins, M. Kallmann, and M. J. Mataric, "Motion capture from inertial sensing for untethered humanoid teleoperation," in *Proceedings of 4th IEEE/RAS International Conference on Humanoid Robots*, Los Angeles, CA, USA, 2004, pp. 547-565.
- [49] T. Cloete and C. Scheffer, "Benchmarking of a full-body inertial motion capture system for clinical gait analysis," in *Proceedings of 30th Annual International IEEE Engineering in Medicine & Biology Society Conference*, Canada, 2008, pp. 4579-4582.
- [50] R. Damgrave and D. Lutters, "The drift of the xsens moven motion capturing suit during common movements in a working environment," in *Proceedings of the 19th CIRP Design Conference*, Cranfield University, 2009, pp. 338-342.
- [51] X. Technologies. (2013). <http://www.xsens.com>.
- [52] S. A. Skogstad, K. Nymoen, Y. de Quay, and A. Jensenius, "OSC Implementation and Evaluation of the Xsens MVN suit," in *Proceedings of New Interfaces for Music Expression*, Oslo, Norway, 2011, pp. 12-35.
- [53] Y. Fujimori, Y. Ohmura, T. Harada, and Y. Kuniyoshi, "Wearable motion capture suit with full-body tactile sensors," in *Robotics and Automation, 2009. ICRA '09. IEEE International Conference on*, 2009, pp. 3186-3193.
- [54] Z. Luo, W. Yang, Z. Q. Ding, L. Liu, I.-M. Chen, S. H. Yeo, *et al.*, "'Left Arm Up!' Interactive Yoga Training in Virtual Environment," in *IEEE Virtual Reality Conference (VR)* Singapore 2011, pp. 261-262.
- [55] L. Liu, K. Yin, M. van de Panne, and B. Guo, "Terrain runner: control, parameterization, composition, and planning for highly dynamic motions," *ACM Transactions on Graphics (TOG)*, vol. 31, no. 6, pp. 154-162, 2012.

- [56] J. Lee, J. Chai, P. S. Reitsma, J. K. Hodgins, and N. S. Pollard, "Interactive control of avatars animated with human motion data," *ACM Transactions on Graphics (TOG)*, vol. 21, no. 3, pp. 491-500, 2002.
- [57] M. Peinado, D. Meziat, D. Maupu, D. Raunhardt, D. Thalmann, and R. Boulic, "Full-body avatar control with environment awareness," *IEEE Computer Graphics and Applications*, vol. 29, no. 3, pp. 62-75, 2009.
- [58] G. Welch and G. Bishop, "An introduction to the Kalman filter," ed. University of North Carolina at Chapel Hill, Chapel Hill, NC, 1995, pp. 1-16.
- [59] Vicon. (2013). <http://www.vicon.com>.
- [60] M. G. Pandy and T. P. Andriacchi, "Muscle and joint function in human locomotion," *Annual review of biomedical engineering*, vol. 12, pp. 401-433, 2010.
- [61] K. Yamane and Y. Nakamura, "Robot kinematics and dynamics for modeling the human body," in *Springer Tracts in Advanced Robotics: Robotics Research*, 2011, pp. 49-60.
- [62] A. Murai, K. Kurosaki, K. Yamane, and Y. Nakamura, "Musculoskeletal-see-through mirror: Computational modeling and algorithm for whole-body muscle activity visualization in real time," *Progress in biophysics and molecular biology*, vol. 103, no. 2, pp. 310-317, 2010.
- [63] Chevy. <http://www.chevyhiperformance.com/>.
- [64] L. Lippert and R. Library, *Clinical kinesiology and anatomy*. Philadelphia: FA Davis, 2006.
- [65] J. Corrales, F. Candelas, and F. Torres, "Hybrid tracking of human operators using IMU/UWB data fusion by a Kalman filter," in *Proceedings of 3rd ACM/IEEE International Conference on Human robot interaction*, Amsterdam, 2008, pp. 193-200.
- [66] G. Yang, "Kinematics, dynamics, calibration, and configuration optimization of modular reconfigurable robots," PhD Thesis, Nanyang Technological University, Singapore, 1999.
- [67] I.-M. Chen, G. Yang, C. T. Tan, and S. H. Yeo, "Local POE model for robot kinematic calibration," *Mechanism and Machine Theory*, vol. 36, no. 11-12, pp. 1215-1239, 2001.

- [68] R. He, Y. Zhao, S. Yang, and S. Yang, "Kinematic-Parameter Identification for Serial-Robot Calibration Based on POE Formula," *Robotics, IEEE Transactions on*, vol. 26, no. 3, pp. 411-423, 2010.
- [69] G. Yang, "Kinematics, dynamics, calibration, and configuration optimization of modular reconfigurable robots," PhD, Nanyang Technological University, Singapore, 2011.
- [70] E. Bachmann, "Inertial and magnetic tracking of limb segment orientation for inserting humans into synthetic environments.," PhD Thesis, Naval Postgraduate School Monterey CA., 2000.
- [71] K. Nguyen, I.-M. Chen, Z. Luo, S. Yeo, and H. Duh, "A wearable sensing system for tracking and monitoring of functional arm movement," *Mechatronics, IEEE/ASME Transactions on*, vol. 16, no. 2, pp. 213-220.
- [72] InterSense. (2013). www.intersense.com.
- [73] "APDM. (2013) www.apdm.net."
- [74] R. Murray, Z. Li, S. Sastry, and S. Sastry, *A mathematical introduction to robotic manipulation*: CRC, 1994.
- [75] M. W. Spong, S. Hutchinson, and M. Vidyasagar, *Robot modeling and control*: John Wiley & Sons New York, 2006.
- [76] J. C. John, "Introduction to robotics: Mechanics and control," *Addison-Wesley Publishing Company, Inc., Reading, MA*, pp. 211-215, 1989.
- [77] R. Drillis, R. Contini, and M. Maurice Bluestein, "Body segment parameters," in *Artificial limbs* vol. Technical Report No. 1166.03., ed. School of Engineering and Science, New York University., 1966, pp. 44-50.
- [78] M. Silaghi, R. Plänkers, R. Boulic, P. Fua, and D. Thalmann, "Local and global skeleton fitting techniques for optical motion capture," *Modelling and Motion Capture Techniques for Virtual Environments*, vol. 1537, pp. 26-40, 1998.
- [79] S. Gamage and J. Lasenby, "New least squares solutions for estimating the average centre of rotation and the axis of rotation," *Journal of biomechanics*, vol. 35, no. 1, pp. 87-94, 2002.
- [80] MotionAnalysis. (2013). <http://www.motionanalysis.com/>.
- [81] J. McCarthy, *Introduction to theoretical kinematics*: MIT Press, Cambridge, MA, 1990.

- [82] O. Bretscher, *Linear algebra with applications*: Prentice Hall Eaglewood Cliffs, NJ, 1997.
- [83] Q. Yuan, I.-M. Chen, and S. P. Lee, "SLAC: 3D Localization of Human Based on Kinetic Human Movement Capture," in *Proceedings of IEEE International Conference on Robotics and Automation*, Shanghai, China, 2011, pp. 848 - 853.
- [84] P. Esser, H. Dawes, J. Collett, and K. Howells, "IMU: inertial sensing of vertical CoM movement," *Journal of biomechanics*, vol. 42, no. 10, pp. 1578-1582, 2009.
- [85] Q. Li, M. Young, V. Naing, and J. Donelan, "Walking speed estimation using a shank-mounted inertial measurement unit," *Journal of biomechanics*, vol. 43, no. 8, pp. 1640-1643, 2010.
- [86] S. Kajita, F. Kanehiro, K. Kaneko, K. Yokoi, and H. Hirukawa, "The 3D linear inverted pendulum mode: a simple modeling for a biped walking pattern generation," in *Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems*, Maui, HI, 2001, pp. 239-246.
- [87] Q. Yuan and I.-M. Chen, "Human Velocity and Dynamic Behavior Tracking Method for Inertial Capture System," *Sensors and Actuators A: Physical*, vol. 183, no. 01, pp. 123-131, 2012.
- [88] Q. Yuan and I.-M. Chen, "Simultaneous Localization and Capture with Velocity Information," in *Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems*, San Francisco, California, 2011, pp. 2935 - 2940.
- [89] G. Welch and G. Bishop, "An introduction to the Kalman filter," pp. 1-16, 1995.
- [90] R. Kalman, "A new approach to linear filtering and prediction problems," *Journal of basic Engineering*, vol. 82, no. 1, pp. 35-45, 1960.

List of Publications

Journal Publications

- [1] Q. Yuan and I.-M. Chen, "Localization and velocity tracking of human via 3 IMU sensors", *Sensors and Actuators A: Physical*, vol. 212, no. 1, pp. 25-33, 2014.
- [2] Q. Yuan and I.-M. Chen, "3D Localization of Human Based on Inertial Capture System," *IEEE Transactions on Robotics*, vol. 29, no. 3, pp. 806-812, 2013.
- [3] Q. Yuan and I.-M. Chen, "Dynamic Behavior Tracking and Localization Method for Inertial Capture System," *Journal of The Chinese Society of Mechanical Engineers*, vol. 34, no. 2, pp. 129-136, 2013.
- [4] Q. Yuan and I.-M. Chen, "Human Velocity and Dynamic Behavior Tracking Method for Inertial Capture System," *Sensors and Actuators A: Physical*, vol. 183, no. 1, pp. 123-131, 2012.
- [5] Q. Yuan and I.-M. Chen, "Planar jumping with stable landing through foot orientation design and ankle joint control," *Frontiers of Mechanical Engineering*, vol. 7, no. 2, pp. 100-108, 2012.

Conference Publications

- [1] Q. Yuan and I.-M. Chen, and W. Ang "Method to Calibrate the Skeleton Model Using Orientation Sensors," in Proceedings of IEEE International Conference on Robotics and Automation, Karlsruhe, Germany, 2013.
- [2] Q. Yuan and I.-M. Chen, "Human Motion Capture, Localization and Interaction Based on Wearable Inertial and Contact Sensors," in Proceedings of Climbing and Walking Robots 2013 Conference, Sydney, Australia, 2013.
- [3] Q. Yuan and I.-M. Chen, and C. Albert, "Full-Body Motion and Velocity Tracking Based on Contacts and Body Kinematics: a Kendo Demonstration," in Proceedings of 3rd IFToMM Int. Sym Robotics Mechatronics Singapore, 2013.
- [4] W. Ang, Q. Yuan and I.-M. Chen, "Ambulatory Measurement of Shoulder Kinematics Using Inertial Measurement Units and Shoulder Rhythm Model," in Proceedings of 3rd IFToMM Int. Sym Robotics Mechatronics Singapore, 2013.

- [5] Q. Yuan and I.-M. Chen, "Dynamic Behavior Localization Method for Inertial Sensor Based Human Motion Tracking System," in Proceedings of the 43rd International Symposium on Robotics, Taipei, Taiwan, 2012, pp. 723-230.
- [6] Q. Yuan and I.-M. Chen, "Simultaneous Localization and Capture with Velocity Information," in IEEE/RSJ International Conference on Intelligent Robots and Systems, San Francisco, California, 2011, pp. 2935-2940.
- [7] Q. Yuan and I.-M. Chen, "Planar Jumping with Stable Landing through Foot Orientation Design and Ankle Joint Control," in Proceedings of 2nd IFToMM Int. Sym Robotics Mechatronics, Shanghai, China, 2011, pp. 292-302.
- [8] Q. Yuan and I.-M. Chen, and S. P. Lee, "SLAC: 3D Localization of Human Based on Kinetic Human Movement Capture," in Proceedings of IEEE International Conference on Robotics and Automation, Shanghai, China, 2011, pp. 848-853.
- [9] Q. Yuan and I.-M. Chen, "Human-like walking of humanoid robot based on biped kinematics and captured motion of human," presented at the Proceedings of the 13th World Congress in Mechanism and Machine Science, Guanajuato, MÉXICO, 2011, pp. 258-266.
- [10] Q. Yuan and I.-M. Chen, "Kinematic Uncertainties in Human Motion Tracking and Interaction," Advances on Theory and Practice of Robots and Manipulators: Proceedings of Romansy 2014 XX CISM-IFTToMM Symposium on Theory and Practice of Robots and Manipulators, pp. 491-499, 2014.

Patent Pending

- [1] I.-M. Chen and Q. Yuan, "Method and Apparatus for Calibrating a Motion Tracking System," ed: WO Patent 2,013,070,171, 2013.