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Wearable Wireless Ultrasonic Sensors for Human Gait Analysis

ASHHAR KARALIKKADAN

School of Electrical & Electronic Engineering

A thesis submitted to the Nanyang Technological University
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy

2020

Statement of Originality

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

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ASHHAR KARALIKKADAN

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

10 March 2020

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Soh Cheong Boon

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Authorship Attribution Statement

This thesis contains material from [5 number] papers published in the following peer-reviewed journals / from papers accepted at conferences in which I am listed as an author.

Chapter 3 is published as [Karalikkadan Ashhar, Cheong Boon Soh, and Keng He Kong \(2018, October\). Wireless Ultrawideband Sensor Network for Gait Analysis in Rehabilitation Clinics. In 2018 IEEE International Conference on Systems, Man, and Cybernetics \(SMC\) \(pp. 1524-1529\). IEEE. DOI: 10.1109/SMC.2018.00264.](#)

The contributions of the co-authors are as follows:

- Assoc. Prof. Soh Cheong Boon provided the initial project direction and edited the manuscript drafts.
- Dr. Keng He Kong provided the guidance and clinical importance of the project.
- I prepared the manuscript drafts. The manuscript was revised by Assoc. Prof. Soh Cheong Boon and Dr. Keng He Kong.
- I co-designed the study with Assoc. Prof. Soh Cheong Boon.
- I performed all the laboratory work at the Motion Analysis Laboratory, School of Mechanical and Aerospace Engineering, and analyzed the data.

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The contributions of the co-authors are as follows:

- Assoc. Prof. Soh Cheong Boon provided the initial project direction and edited the manuscript drafts.
- Dr. Mohammad Omar Khyam provided the idea for multi-path compensation and assisted in simulation experiments.
- I co-designed the experiments along with Dr. Mohammad Omar Khyam.
- I prepared the drafts of the manuscript. The manuscript was revised together with Dr. Mohammad Omar Khyam and Assoc. Prof. Soh Cheong Boon.
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- Assoc. Prof. Soh Cheong Boon provided the initial project direction and edited the manuscript drafts.
- Dr. Keng He Kong verified the clinical importance of the project and provided feedback on the clinical accuracy required for tracking.
- I co-designed the study along with Assoc. Prof. Soh Cheong Boon.
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- Dr. Mohammad Omar Khyam assisted in conducting simulation experiments.
- The experiment was co-designed by Dr. Md Noor-A-Rahim, Dr. Mohammad Omar Khyam, and I.
- I prepared the drafts of the manuscript. The manuscript was revised together with Dr. Md Noor-A-Rahim, Dr. Mohammad Omar Khyam and Assoc. Prof. Soh Cheong Boon.
- I conducted all the experiments, collected and analyzed the data.

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- Dr. Keng He Kong provided the clinical importance of the system, its applications and the clinical accuracy required.
- Dr. Mohammad Omar Khyam assisted in signal design and design of ranging experiments.

- The experiment was co-designed by Dr. Mohammad Omar Khyam and I.
- I conducted all the experiments, collected, and analyzed the data.
- I prepared the drafts of the manuscript. The manuscript was revised together with all the other authors.

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“Imagination is more important than knowledge. Knowledge is limited. Imagination encircles the world.”

—Einstein, Albert

To my dear father and mother for all the encouragement and
support

Abstract

Human motion capture has been used in rehabilitation clinics for evaluating, quantifying the severity of various neuromuscular and musculoskeletal diseases, and monitoring the progress of recovery. High accuracy motion tracking is necessary for gait analysis. The analyses of bilateral gait symmetry, coordination, and lower extremity joint angles during gait are important in rehabilitation after trauma, prosthesis, and other neurovascular diseases such as stroke. It can also act as a precursor to the freezing of gait in Parkinson's disease. Current methods for gait analysis include optical motion tracking systems using multiple high-speed cameras, instrumented platforms, etc. which are complicated, costly and require controlled lighting conditions and dedicated laboratories. Systems using multiple cameras are sensitive to variations in the intensity of light, occlusion, and shadow. Recent advancements in the field of micro-electromechanical systems led to the use of inertial measurement units like accelerometers and gyroscopes for human motion tracking. However, the unavoidable integration drift in the calculated position values made the independent use of these systems unfit for human motion capture. The combination of various kinds of sensors to improve reliability makes the system more complex and costly. Narrowband ultrasonic sensors can be used for accurate ranging with considerably cheaper hardware.

This research proposes a scalable, cost-effective, wearable ultrasonic gait analysis system, which is easy to use, portable, and does not require complex calibration procedures. The system uses four fixed anchors to track multiple mobile nodes. The Time of Arrival of ultrasonic pulses has been used for localization with the help of spherical positioning and Unscented Kalman filter. Initially, we compare the performance of a wireless ultrawideband (UWB) system and a wireless ultrasonic system for gait analysis. Ultrasonic sensors have been found to provide better performance compared to UWB for low-cost wireless implementations. Broadband ultrasonic sensors perform better with correlation receivers; however, they are costly and requires higher operating voltages and cannot be used for wearable

applications, and this motivates us to design a scalable gait analysis system using narrowband ultrasonic sensors.

The standard method for time of flight estimation is the correlation where the transmitted and the received signals are correlated to provide a peak delayed by the time of flight of the wave. In correlation receivers, the accuracy of ranging is inversely proportional to the width of the correlation peak and the width of the correlation peak is again inversely related to the bandwidth of the signal. An increase in the width of correlation peak due to the lower bandwidth of the signals prevents the identification and separation of close multi-path components at the receiver side. In the initial part of this thesis, a gait analysis system has been designed with one wearable mobile node where a novel method to compensate for the errors caused by close multi-path components has been proposed. Moving sensors emitting ultrasonic signals also cause Doppler shift in the received signal which affects the accuracy of ranging. We propose two methods for Doppler shift correction using chirp signals. Narrowband ultrasonic chirp signals have been used for ranging and localization of one mobile node along with a novel multi-path compensation and Doppler correction technique during gait analysis of healthy human subjects. Four passive anchor nodes and one active mobile node have been used. The mean values of the Root Mean Square Error (RMSE) with reference to the motion capture system obtained for tracking one mobile node using chirp signals were found to be 19.32, 9.79, and 18.40 mm which was again reduced to 16.04, 8.14, and 12.92 mm respectively for x, y, and z-axes after removing close multi-path components in the received signals using the proposed multi-path compensation method. The proposed Doppler correction methods were also compared to traditional methods using a pendulum experiment.

To increase the number of mobile nodes, we test spatial division multiple access in the initial experiments in the second part of the thesis where sensors are arranged spatially in a way that multiple mobile nodes can transmit at the same time without interference. For tracking both the lower limbs simultaneously during gait analysis employing two mobile nodes using monotonous ultrasonic pulses and spatial division multiple access, net-RMSE was found to be 27.67, 32.01, and 35.63 mm for walking speed of 1, 2, and 3 kph. A pilot simulation study has been conducted to find the performance of tracking the hip and knee joint angles with a minimum number of mobile nodes attached to the body. To reduce the number of

anchor nodes and make the system robust, we have designed an ultrasonic system in which orthogonal coded chirp signals are used for simultaneous multiple access and Doppler-correction. The ranging performance with the method is validated using a pendulum experiment with four ultrasonic transmitters. The method has been tested on healthy subjects for bilateral gait symmetry analysis and base of gait estimation using only two mobile tags and four anchor nodes. The mobile nodes were attached to the feet of the subject, and the anchor node plane was placed behind the subject walking on a treadmill. The results were compared with the Motion capture system and mean net-RMSE between the trajectories was found to be 30.30, 28.55, and 32.01 mm respectively for walking speed of 1, 2, and 3 kph. The spatial and temporal parameters extracted from the proposed method have been compared to the reference system.

Experiments were conducted to evaluate the performance of the gait analysis system with proposed methods for signal design, Doppler correction, multiple access, and multi-path compensation compared to the optical motion capture reference system. The experimental results show that the proposed system can be used to assess the human gait symmetry and other spatial and temporal parameters in a convenient setup for a long duration with minimal errors. Moreover, a bilateral gait deviation measure has been proposed to quantify the deviations between the trajectories of the left and the right lower limbs. The deviation measures from both systems were determined for five healthy subjects and one subject with a simulated leg length discrepancy, and these values were compared. In summary, this research proposes, evaluates and validates a convenient and scalable ultrasonic gait analysis system for rehabilitation clinics.

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Symbols and Acronyms

Symbols

$\star$	the correlation operation
$*$	the convolution operation
$^{\circ}C$	Degree Celcius
$N(m, V)$	Gaussian Distribution with m mean and V variance
$diag()$	Diagonal matrix
$^{\circ}$	Degrees

Acronyms

LOS	Line of Sight
NLOS	Non-Line of Sight
ToF	Time of Flight
3D	Three-dimensional
ToA	Time of Arrival
TDoA	Time Difference of Arrival
TWR	Two-way Ranging
AoA	Angle of Arrival
RSSI	Received Signal Strength Indicator
UWB	Ultrawideband
EKF	Extended Kalman Filter
UKF	Unscented Kalman Filter
URTS	Unscented Raunch-Tung-Striebel Smoother
BPSK	Binary Phase Shift Keying
CDMA	Code Division Multiple Access

SDMA	Spatial Division Multiple Access
DSSS	Direct Sequence Spread Spectrum
FHSS	Frequency Hopping Spread Spectrum
OFDM	Orthogonal Frequency Division Multiple Access
PVDF	Polyvinylidene Fluoride
EMFi	Electromechanical Films
cMUTs/pMUTs	capacitive/piezoelectric Micromachined Ultrasonic Transducers
IMUs	Inertial Measurement Units
ADC	Analog to Digital Converter
PAPR	Peak to Average Power Ratio
AWGN	Additive White Gaussian Noise
SNR	Signal to Noise Ratio
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
kph	Kilometers per hour
PCC	Pearson's Correlation Coefficient
ECDF	Empirical Cumulative Distribution Function

Chapter 1

Introduction

The increased demand for health care services leads to the reduction of the need for face-to-face therapy to increase efficiency and reduce the cost. Therefore more interest has been drawn towards home-based rehabilitation schemes. Rehabilitation is a dynamic process to correct body movement impairments to reach an expectation [8]. Consequently, it is very much essential to track the body movements to be adjusted continuously during rehabilitation [8]. Recently researchers are more focused on the development of low-cost, portable and yet accurate human motion capture systems in a homely setup.

The pattern in which a person walks is known as gait. Gait analysis can be defined as the systematic measurement, description, and assessment of the factors which characterize human locomotion. It is an evaluation tool to evaluate quantitatively the extent of gait abnormality caused by some diseases or rehabilitation progress [9]. Various diseases can affect the spatial and temporal components of the gait independently, so it is important to analyze both components of gait trajectory [10]. The study of gait can be used to evaluate the presence, occurrence, or recovery from many diseases. Some of the diseases which affect the gait of a human being are multiple sclerosis, amyotrophic lateral sclerosis, Parkinson's disease, myelopathies, spinal amyotrophy, cerebellar ataxia, brain tumors, cranioencephalic trauma, myopathies, cerebrovascular pathologies, certain types of dementia, heart disease and physiological aging [11].

1.1 Motivation

Human motion tracking is widely used in rehabilitation clinics to quantify the musculoskeletal function in different kinds of patients suffering from neurovascular diseases, injuries, etc. Simple visual observation was used earlier days in clinics for qualitative analysis. However, quantitative gait analysis can provide intricate details about a person's gait [12]. Accurate motion tracking systems in rehabilitation clinics can provide detailed analysis of various gait patterns, monitoring the recovery from abnormal conditions, identifying causes of gait abnormalities and plan further interventions in the course of treatment [13].

The gold standard for human motion capture and gait analysis is the optical motion tracking system using multiple high-speed infrared cameras and reflective markers placed at particular anatomical positions [14]. Various parameters of the gait kinematics can be extracted from the software associated with these systems. However, optical systems require dedicated laboratories, controlled lighting conditions, and skilled operators as they are easily affected by variations in light intensity, clutter, shadow, and complex calibration procedures are involved [15–17]. Motion capture systems such as Vicon MX - with more than six cameras which provide sub-millimeter accuracy cost tens of thousand dollars [18]. Alternate motion tracking sensors include inertial measurement units, magnetic sensors, optical sensors like Microsoft Kinect, laser sensors, glove based sensors, ultrawideband sensors, ultrasonic sensors, etc. [8].

With the recent developments in microelectromechanical systems, inertial measurement units (IMUs) like accelerometers and gyroscopes were used for human motion tracking. IMUs suffer from error accumulation over a long duration of monitoring and are not robust enough for clinical gait analysis [19]. To offset the error accumulation and drift of position measurements in IMUs, various methods have been proposed in the literature, such as zero velocity update or by combining measurements from various kinds of sensors using Kalman filters [20, 21]. However, the zero velocity update will not provide satisfactory results in some abnormal gait patterns where the heel strike does not happen at the initial contact and for long-term evaluation of gait [22]. Sensor fusion with various types of sensors was found to provide higher performance for human motion tracking [23–25]. Such systems provided more accuracy and reliability in exchange for increased complexity and

cost. Microsoft KinectTM can be used as a low-cost optical sensor for gait analysis since it is portable, inexpensive, and marker-free. However, the proportional biases for some outcome measures, occlusion and its inability to assess the internal/external joint rotations in the peripheral limbs are the drawbacks which make this system an unsuitable option for motion capture and gait analysis [26]. UWB antennas were used as wearable nodes for motion tracking in some of the previous works [16, 27], the main drawbacks of which were the inability to synchronize the receiver and the transmitter accurately due to the high speed of UWB signals, high cost and difficulty in designing an analogue to digital converter for sampling such a high bandwidth signal [28]. Sensor fusion of various types of sensors was implemented previously [23–25]. These systems were able to provide more accuracy and reliability in exchange for increased complexity and cost. All markerless motion capture systems proposed in the literature were found to provide less accuracy compared to the systems using markers. A model-based markerless motion capture system was proposed in [29], in which the accuracy of tracking depends on the resolution of the camera used and increasing the resolution and constructing the model makes this system complex.

Time of flight based ultrasonic positioning systems can be cost-effective alternatives for long-term motion tracking in rehabilitation clinics and gait analysis [30]. Accurate ranging using ultrasound systems are possible as the speed of propagation of the ultrasonic wave is lower compared to electromagnetic waves. Walls and other obstacles block ultrasonic waves and thus they are easier to model and control. Ultrasonic systems can also be used in some places where RF systems cannot be used like hospitals [31]. Acoustic systems were used for indoor localization in some of the previous works such as the Cricket system [32], The BAT system [33], etc. Precise calculation of ToF requires accurate clock synchronization between the transmitter node and the receiver node. Wireless localization systems are prone to errors in clock synchronization, which leads to errors in ToF. The error in the estimation of range can be given by, $\delta d = v \times \delta t$, where δt is the error in the time of flight and v is the velocity. Here, as the velocity of the wave increases, the error in the estimated range also increases. Hence slower waves such as ultrasound can withstand much more errors in ToF compared to electromagnetic waves. Cross-correlation of the received signal with the initially transmitted signal is considered a standard method for calculation of range. Frequency modulated linear chirps give

better cross-correlation performance and efficiency in time-varying fading channels compared to single-tone signals [5]. Polyvinylidene Fluoride (PVDF) [34], Electromechanical Film (EMFi) [35] and capacitive/piezoelectric Micromachined Ultrasonic Transducers (cMUTs/pMUTs) [36] can be used to design ultrasonic sensors with higher bandwidth which can provide better noise tolerance, data update rate and wireless channel multiple access using various signal processing methods such as Direct Sequence Spread Spectrum (DSSS) [37, 38], Frequency Hopping Spread Spectrum (FHSS) [38, 39], Code Division Multiple Access (CDMA) [40] etc. However, the cost of the system increases significantly, and higher operating voltages make the system unfit for mobile and wearable applications. Thus, increasing the bandwidth of ultrasonic sensors for localization applications is difficult leaving narrowband ultrasonic sensors as the best option for small-scale motion tracking. Enabling channel multiple access for increasing the number of mobile nodes in a localization system is challenging with narrow bandwidth. Ultrasonic sensor network with one transmitter attached to one foot and four fixed anchors at known positions were used for gait analysis in [28]. Here, signals with single-tone frequency at 40 kHz were used along with narrowband piezoelectric sensors. However, this system can measure the three-dimensional (3D) coordinates of only one marker. To monitor the bilateral symmetry and coordination or to track joint angles during gait, we need more than one mobile node to be attached to the body and tracked. At the same time, we need to minimize the cost and complexity of the system, making it wearable and portable.

Thus, it is essential to develop a cheap, portable, and convenient system which is scalable for tracking multiple markers for gait analysis in a homely setup. Hence our research focuses on reducing the cost and complexity of human motion capture system while retaining the required accuracy. It is therefore of interest to study various signal designs and coding schemes for narrowband ultrasonic sensors to increase the ranging accuracy, facilitate multiple access and compensate multipath interference for applications in human motion tracking and gait analysis. In this thesis, various signal designs are investigated for low range measurements using narrowband ultrasonic sensors. A gait analysis system using two mobile nodes attached to lower limbs was designed and tested for extracting spatial and temporal parameters, gait symmetry and coordination.

1.2 Objectives

The objectives of this thesis can be summarized as follows:

1. In this thesis, we aim to design a robust gait analysis system using wireless wearable sensors, which is not affected by changes in lighting conditions and does not require dedicated laboratories and complex calibration procedures.
2. Design a wireless gait analysis system using ultrawideband sensors and compare it with similar systems using ultrasonic sensors.
3. We study a narrowband ultrasonic sensor network to track multiple sensor nodes using various signal processing techniques to tackle problems like the multiple-access and multi-path interference, and the Doppler shift.
4. . Investigate methods to compensate close multi-path components in narrow-band ultrasonic correlation receivers and design a gait analysis system with a single wearable mobile node and benchmark the performance using optical motion capture system.
5. Evaluate the performance of spatial division channel multiple access with single-tone ultrasonic pulses in wearable ultrasonic gait analysis system for bilateral gait tracking and benchmark with the gold standard motion tracking system.
6. Investigate the possibility of tracking lower limb joint angles using only two wearable ultrasonic sensor nodes and spatial division multiple access.
7. We also aim to study the feasibility to scale the number of wearable markers in the proposed gait analysis system without affecting the accuracy, data update rate, and complexity. We investigate methods to scale up the number of mobile nodes one set of four receivers can track which enables us to track closely moving mobile nodes without interference. Time division multiple access decreases the data update rate of the system and hence we need to modulate the ultrasonic signals using some orthogonal codes. We study the performance of orthogonal coded chirp signals for simultaneous multiple access and Doppler correction when more than two moving ultrasonic sensors transmit ranging signals simultaneously.

8. Evaluate the method of simultaneous multiple access and Doppler correction for bilateral gait analysis with minimum hardware complexity and derive various parameters of gait including bilateral gait deviation measure and compare it with that of the motion capture system.

1.3 Major contribution of the Thesis

1. We proposed the exploitation of two Doppler compensation methods for ranging between a static receiver and a moving mobile node. The two methods are: (1) Pilot carrier-based method and (2) Range-Doppler coupling compensation method. The first method was adapted from OFDM signal processing for ultrasonic sensors and the second method was adapted from radar signal processing. The performance of the methods is compared with the traditional Doppler correction methods using a pendulum experiment. The method which provides the best performance is selected and implemented in the proposed gait analysis system.
2. We proposed an adaptation of a multi-path compensation method from radar signal processing to ultrasonic ranging with one mobile node transmitting chirp signals using correlation receivers. The proposed method was implemented and tested using simulation and hardware and the improvements in accuracy and precision are quantified. The method was also implemented in the ultrasonic gait analysis system with one mobile node attached to the lower limb of human subjects. The system was tested with five healthy subjects for varying walking speeds.
3. A narrowband ultrasonic system with two mobile nodes and eight anchor nodes was designed for gait analysis. The system can track two mobile nodes simultaneously using spatial division multiple access. The accuracy of the system was tested and validated for bilateral gait symmetry assessment and human knee joint flexion and extension angle calculation. Gait parameters were extracted from the 3D trajectories. We found that the spatial arrangement of sensors can enable multiple-access in a motion tracking system if sensors are placed at a minimum separation. A method to track the hip and knee joint angles is also proposed and studied with an optical motion capture database.

4. A method for simultaneous multiple access and Doppler-correction in the narrowband ultrasonic ranging system was proposed and tested using a pendulum experiment with multiple transmitters and one receiver. Four narrowband ultrasonic sensors were made to transmit orthogonal coded chirp signals simultaneously, and the received signals were analyzed for the time of flight calculations. This method can be used for simultaneous Doppler correction and multiple access using narrowband ultrasonic sensors using linear chirp signals and correlation receivers when more number of transmitters need to transmit ranging signals at the same time.
5. A technique for simultaneous Doppler-correction and multiple access in narrowband ultrasonic tracking system using chirp signals with two mobile nodes was implemented in a bilateral gait analysis system. The system was tested for performance using five healthy subjects at varying walking speeds. Various bilateral symmetry/deviation measures and spatial and temporal gait parameters are derived from the 3D trajectories of the lower limbs and compared with that of an optical motion capture system. A bilateral gait deviation measure was proposed and benchmarked with the optical system.

1.4 Organization of the Thesis

The report is organized as follows:

1. Chapter 1 introduces the basic research problem and scope of our research, motivation, and objectives. A brief description of the previous methods for motion capture is also discussed.
2. Chapter 2 gives a literature survey on human motion tracking and gait analysis systems. It provides a detailed study of various sensors employed for gait analysis and motion tracking, their advantages and disadvantages.
3. Chapter 3 gives an overview of the methods of ranging and localization algorithms, gait phases, and gait parameter extraction which are used in this thesis. The second part of Chapter 3 presents a comparative study of wireless UWB and similar ultrasonic sensors for gait analysis.

4. Chapter 4 proposes two Doppler compensation methods for a single mobile node and multiple anchor nodes. The performance of the proposed methods is compared with existing methods for Doppler correction.
5. Chapter 5 explains a novel multi-path compensation technique for narrow-band ultrasonic sensor network with only one mobile node. One of the Doppler compensation methods explained in Chapter 4 is also employed in this system. Gait phase segmentation and extraction of spatiotemporal parameters from the 3D trajectory of gait are done, and results are analyzed.
6. Chapter 6 demonstrates the methods of bilateral gait symmetry during gait employing spatial division multiple access with ultrasonic sensors. A pilot study for joint flexion and extension angle calculation of lower limbs is also presented.
7. Chapter 7 explains some multiple access and Doppler correction methods using chirp signals.
8. Chapter 8 explains the design of a bilateral gait analysis system using chirp signals employing the methods explained in Chapter 7 and gait parameters and bilateral gait deviation measure are extracted.
9. Chapter 9 concludes the report and suggests some ideas for future work.

Chapter 2

Literature Review

2.1 Overview of Different Methods for Ranging

Range-based localization requires accurate measurement of the distance between a target and several reference nodes. Ranging is defined as the estimation of the distance between two wireless nodes using some waves [13]. There are different methods for ranging and localization: Received-Signal-Strength-Indicator (RSSI), Angle of Arrival (AOA), one-way Time of Arrival (ToA), two-way ranging (TWR), double-sided TWR [41], Time Difference of Arrival (TDoA) [42] and a combination of Time Difference of Arrival (TDoA) and Frequency Difference of Arrival (FDoA) [43]. RSSI uses received signal power to estimate the range and is less complex than other methods; however, it is unable to provide the accuracy required for human motion capture [27]. AOA requires costly antenna arrays and are not preferred for low-cost applications [41]. With the help of a common time reference, one-way ToA can be used for accurate ranging where the time difference between the transmission and the reception is converted to distance by multiplying with the velocity of the wave. In TWR, the first node transmits one packet with the time information to the second node, and the second node sends back an acknowledgement after a fixed duration. In double-sided TWR, the transmitter sends one more signal after the TWR [44]. TDoA calculates the relative difference between the arrival of several signals. When the target is moving, FDoA can be used to get the accurate position and velocity estimates. In this work, we employ one-way ToA with ultrasonic waves as it can provide high accuracy due to the lower

speed of ultrasonic waves and ToA can provide higher data update rate compared to TWR. Ultrasound is slower compared to electromagnetic waves, and thus small drifts in the clock do not incur much error in the range measurements [13]. Hence, clock synchronization can be done using cheaper hardware.

2.2 Sensors for Motion Tracking and Gait Analysis

Different kinds of sensors can be used for 3D human motion capture and gait analysis. Commercial 3D motion capture systems such as VICON are widely used and are quite accurate [45]. However, their cost and complexity led to a vast area of research in portable and cheap motion capture systems for clinical gait analysis. Gait analysis assists physiotherapists to validate the treatment prescribed for patients objectively. Some popular methods of motion tracking, their advantages and disadvantages are reviewed here.

2.2.1 Visual Marker-Based Systems

In systems using multiple infrared cameras, markers are placed on the human body at the points to be tracked. Such systems are considered as the gold standard in human motion tracking systems due to the ability to provide high (sub-mm) accuracy [14]. The types of markers used can be passive or active. VICON system uses reflective markers with multiple infrared cameras and is an example of a passive optical system [45]. An example of an active visual tracking system is CODA motion sensors [46]. The dependence of performance on variations in the light intensity, clutter, and occlusion of markers are the main problems with these systems [15, 16]. Dedicated laboratories, experienced operators, and complex calibration measures are required for these systems. The rotated joints or overlapped body parts cannot be detected, making the creation of 3D model difficult and complex [8].

2.2.2 Visual Marker-Free Systems

These systems avoid the effort and inconvenience for accurate placement of markers on the subject's body by compromising on the accuracy and computation needs of the system. Computer vision techniques are employed to obtain motion parameters from video footage [47]. This technique requires high-speed cameras and intensive computation [8]. In [48], markerless motion capture of articulated skeleton motions of several subjects in indoor as well as outdoor scenarios were studied. The system used 2-3 cameras and convolutional networks and achieved an average joint position error of a few centimeters. However, the frame-rate of the camera needs to be adequate to handle the speed of the target and more number of cameras are required as occlusion and ambiguities can cause spurious results while reconstruction. Also, the variations in the light, occlusion, and clutter affect marker-free systems as well. A depth-sensing camera like Microsoft KinectTM can also be used for markerless motion analysis. Microsoft KinectTM is a motion sensing input device which is widely used in computer gaming technology. It is portable, inexpensive, and marker-free. However, the proportional biases for some outcome measures and the inability to assess the internal/external joint rotations in the peripheral limbs are the two drawbacks which make this system not a suitable option for motion capture and gait analysis [26]. Also, the tracking accuracy does not suffice for clinical movement analysis applications [49]. Colored markers were tracked accurately with Kinect in [50]. However, controlled environment and lighting conditions are required for this as the background color affects the tracking performance of different markers.

2.2.3 Inertial Measurement Units

The motion tracking systems using IMUs such as accelerometers and gyroscopes have been used for human motion analysis in previous works [19, 51–53]. They can be used in unrestrained environments without limitations of boundaries, high sensitivity, and sampling rate. The acceleration can be double integrated to obtain the position, and angular velocity can be integrated to get the flexion angles. Miniaturization of sensors was possible with the recent developments in the field of Microelectromechanical systems (MEMS). However, as there is a need for integration of acceleration and angular velocity to obtain the position and angle, the

fluctuations in offsets and unavoidable measurement noise make way for integration drift unless otherwise corrected by some other type of sensors [13]. The error accumulation and variable offsets make these systems unfit for long-term motion analysis and incur the need for re-calibration. The error accumulation was corrected in some of the previous works using zero velocity update, in which the assumption of heel strike at initial contact and toe-off at the terminal contact was made. This assumption may not be valid in some of the abnormal gaits [54]. They are also affected by fluctuations in the offset values [55]. Multiple sensor fusion needs to be done using inertial sensors to get satisfactory tracking performance [56, 57], which increases the cost and complexity of the system. Shimmer[®] sensor nodes with 3 axis accelerometers and 3 axis gyroscopes were used to evaluate the symmetry and normalcy of gait in [58]. Xsens MVN (Xsens Technologies, Netherlands) employed many sensors with 3D accelerometers, 3D gyroscopes, and 3D magnetometers for implementation of sensor fusion. The system requires an initial calibration each time measurement starts as the initial pose of the sensors and body segments are unknown [57]. Full body suits with sensor nodes attached at specific points are also commercially available [57].

2.2.4 Magnetic Sensors

Magnetic motion tracking systems have been widely used in virtual reality, due to their size, high sampling rate and lack of occlusion [59]; however, they are affected by the heterogeneity of the earth's magnetic field and other ferromagnetic materials present in the environment [60]. Latency and jitter are the main drawbacks of these systems. Latency arises due to the asynchronous measurements, and jitter appears in the presence of ferromagnetic materials present in typical indoor environments [8]. A magnetic motion capture system with two markers and three-axial magnetic field sensors were used in [61]. The main source of error was the cross-talk between the cores of three axial sensors.

2.2.5 Wearable Force and Pressure Sensors

Force sensing platforms or wearable force sensors can be used to get the ground reaction forces, the center of pressure and the joint moments [62, 63]. They provide ground reaction forces and do not provide 3D coordinates of any markers. The type of sensor used can be force sensitive resistors, piezoelectric sensors, or capacitive sensors. Force sensitive resistors such as foot switches or in-shoe foot plantar pressure sensor [64] were used in gait analysis to estimate the spatiotemporal parameters or kinetic parameters like joint moments. Even though their output is easy to process, they provide the data only during the stance phase of gait. They are not convenient to wear and may end up in mechanical failure in some cases. abnormalities like drop foot and shuffling feet may provide unreliable results with foot switches [65]

2.2.6 Laser Sensors

Laser sensors can be used for gait analysis [66, 67]. Mis-detection of a body part to be tracked can lead to large outliers in the measured data [66]. Also, the laser sensor takes a long time to take one sample of the whole scenario due to their scanning pattern [68].

2.2.7 Electromyography(EMG)

EMG, which is the electrical activity of the contracting muscles, can be measured non-invasively using surface electrodes. It can be used to classify kinematic parameters indirectly. EMG was able to predict the initial movement in transfemoral amputees 138 ms in advance compared to kinematic sensors when the prosthetic leg leads [69]; however, EMG cannot provide the 3D trajectories and are subject-specific.

2.2.8 Robotic Aided Systems

Robotic aided tracking systems can be used for delivering neuro-rehabilitation after stroke [70]. A robotic stepper that uses a pair of robotic arms resembling knee

braces, to guide a patient's legs was designed to automate body weight support training [71]. The sensors attached can measure force, speed, acceleration, and resistance and were tested for gait analysis. Knee braces were used to track knee angles in [72]. Potential limitations of mechanical systems are that they can block the free movement of the limbs, affects the normal gait, and they are less compact.

2.2.9 Ultrawideband Radio Systems

UWB radio is popular for its data rate, robustness to fading, security, penetration without significant loss, low power consumption, multiple access, scalability feasibility, and higher range [73]. UWB ranging sensors can be used for human motion tracking [27]. An accurate localization approach using UWB signals and TDoA was explained in [74]. The system was able to achieve sub-centimeter accuracy. However, these systems require highly accurate clock synchronization between the mobile nodes and anchors, which is extremely challenging in low-cost systems due to the high propagation speed of the UWB waves. Commercial UWB localization systems have reported 10-15 cm accuracy in the 50m range [75]. For small-scale localization, an accuracy of 1-3 cm was obtained for human limb movement tracking with four base stations in [76]. The measurements were taken at various positions. A carrier-based localization system with UWB was designed to achieve sub-millimeter accuracy [75]. Hence UWB can provide sufficient accuracy for motion capture in the Line of Sight(LOS) conditions. A wearable gait analysis system for ranging between limbs for estimation of gait parameters such as step length and base of support was explained in [27]. 3D tracking using UWB sensors with respect to fixed reference coordinate system was found to provide sub-millimeter accuracy in [77], where the author used a two-phase localization algorithm with a wired clock synchronization at the initial phase; also, wide-bandwidth signal analyzers were used. Furthermore, it is challenging to sample the received signal with current ADC technology as the bandwidth of the signal is very large [30, 78].

2.2.10 Ultrasonic Systems

Ultrasonic systems can be used for range measurement by calculating the time taken by a pulse to travel from the mobile node to the anchor nodes and subsequently converting this measure to distance. The low propagation speed and bandwidth of ultrasound signals allow the use of analog to digital converters at lower sampling frequencies [79]. Ultrasonic sensors can provide high accuracy ToF measurements without using expensive hardware as the wave travels much slower compared to electromagnetic waves, and thus it can tolerate small errors in clock synchronization between the transmitting and receiving nodes [80]. Ultrasonic sensors are preferred due to its safety, low cost, and higher ranging accuracy for low range tracking. Some of the challenges in using ultrasound systems for gait analysis are [8]:

- Larger surface area is required for sensors for efficient tracking.
- The detection range is inversely proportional to the frequency of ultrasound. So for increasing the range, the frequency should be low, which affects the system latency adversely.
- The line of sight between the transmitter and receiver can be blocked by obstacles.
- It is difficult to send information or code the ultrasonic waves for multiple access.
- Wideband sensors require higher polarization voltage to operate.

We use narrowband ultrasonic sensors with 40 kHz center frequency. The spatiotemporal parameters of gait were extracted from the position of the right and left feet in a previous work using ultrasonic sensors [81]; however, this system only tracked the distance from one fixed point to each foot and did not extract the 3D coordinates. Gait analysis system using narrowband ultrasonic sensor network with one mobile node tracked by four fixed anchors was proposed in [22]. However, the system explained the tracking of only one mobile node with monotonic ultrasonic pulses at 40 kHz. The major challenge in tracking multiple targets using narrowband ultrasonic sensors lies in enabling channel multiple access, removing

multi-path interference, and Doppler correction. Methods of multiple access can be space division, time division, frequency division, code division, etc. Time division multiple access significantly reduces the sampling rate of the system. The reduction in sampling rate is due to the low speed of ultrasonic waves so that each pulse occupies the channel for around 20 ms and it is difficult to encode the information regarding the identity of individual transmitters [82].

Channel multiple access was implemented in some of the previous works using broadband ultrasonic sensors. Spread spectrum techniques like DSSS [37], FHSS [39, 83] and CDMA [40] can be supported by broadband ultrasonic sensors to provide better noise tolerance, update rate and channel multiple access. However, the hardware cost increased significantly, and higher voltages and computing requirements made the system unfit for wearable applications. Also, the accuracy while locating fast-moving targets using broadband ultrasonic signals is degraded by the Doppler effect [82]. PVDF, EMFi, and cMUTs/pMUTs can be used as broadband ultrasonic transducers for indoor localization. However, PVDF and EMFi need high bias voltage supply to work, which makes these systems unfit for mobile tracking applications. Also, the mechanical setup needed in case of PVDF due to the length variations of films makes it difficult to use in custom tracking applications [84]. cMUTs can provide a higher bandwidth compared to pMUTs; however, cMUTs require a high bias voltage and which makes the sensors unfit for biomedical application. cMUTs also require complicated and precise fabrication process [85]. pMUTs, on the other hand cannot provide high bandwidth using a single transmitter due to large acoustic impedance mismatch and divergence of the transmitted beam [36, 85]. In [83], a resistor and an inductance were added in series with the narrowband ultrasonic sensor to increase the bandwidth of the transmitter, but these components will introduce additional transmitter power loss. Orthogonal frequency division multiplexing (OFDM) can be used to efficiently use the bandwidth of narrowband ultrasonic sensors for the time of flight measurements between multiple transmitters and fixed anchors. In [86], the author was able to get sub-millimeter accuracy with multiple transmitters using OFDM for static sensors. In [86], the author uses 10 kHz frequency band of narrowband ultrasonic sensors to obtain sub-centimeter accuracy for tracking multiple static transducers. However, the system was not applied for wearable or motion tracking applications. In recent work, Three ultrasonic sources and three ultrasonic receivers were used to obtain six degrees of freedom for pose estimation and motion capture using narrowband

ultrasonic sensors [49]. Here, each mobile receiver node captures the encoded ultrasonic transmissions from a distributed transmitter array of three transmitters to obtain nine distance measurements simultaneously. The positions of transmitters and the microphone array configuration, the 3D coordinates and corresponding angles about three axes (six degrees of freedom) were extracted using these distances; however, the system used a wired connection for synchronization, a spread spectrum technique was used in combination with frequency multiplexing, the system was tested for static pose estimation, and the accuracy was degraded by the non-linear effects of the transducer in the selected frequency band. The performance of the system in the presence of Doppler shift when the targets are moving was not addressed. The accuracy of the orientation estimates calculated from the system was found to be not enough for clinical applications. Some of the existing narrowband ultrasonic indoor localization systems are Active bat [33], Cricket [87], *Randell's* system [88], *Smith's* system [89], AHLoS system [90], iBadge [91], *Huitema's* system [81], DOLPHIN [92], *Whitehouse's* system [93], WALRUS [94], BUZZ [95], Sonitor [96], Spider Bat [97], Interacting multiple model system [98], *Kim's* system [99], *Qi's* system [13]. In all the above-mentioned systems, simple ultrasonic pulses at the resonance frequency of the sensor were used for ranging and no other information was sent through the ultrasonic waves, this limits the tracking accuracy and the update rate of the system. Narrowband ultrasonic sensors were coded for improved accuracy and channel multiple access in *Sato's* system [100], *Aly's* system [101], and *Khyam's* system [102]; however, the effects of Doppler-effect while tracking moving targets and its applications in gait analysis were not studied in detail.

2.2.11 Sensor Fusion

Sensor Fusion is the process by which more than one type of sensors are combined to get better performance compared to that of individual sensors. Systems employing more than one type of sensors to complement the performance of each other such as the systems explained in [24, 25, 55, 103] increased the overall cost and complexity of the system. To improve the tracking performance and compensate for the error accumulation of IMU-based systems over long measurement duration, many researchers used sensor fusion of IMUs with other types of sensors. A stereo camera aided inertial tracking system was presented in [104]. An indoor pedestrian

localization using IMUs and RFIDs was presented in [24]. The joint positions obtained from Kinect sensors were fused with wearable inertial sensors for calculation of joint angles in [105]. Magnetic sensors can be used along with inertial measurement units to obtain sub-centimeter accuracy [106]. All these systems were able to obtain better performance in exchange for increased complexity and cost of the system. Ultrasonic range sensors were used to reduce the error accumulation of IMUs in some of the previous works [25, 103], where the systems were used for navigation of emergency responders without requiring a prepared environment. Sensor fusion of inertial measurement units with ultrasonic sensors was implemented for self-referenced motion tracking by Intersense, Inc. in its commercial products IS600 and IS900 sensors. Here the integration drift was corrected by the ultrasonic ranging system. An acoustic-inertial system, ConstellationTM has been developed for augmented reality applications which was based on an array of fiducial markers on the ceiling to track a head-mounted device along with inertial sensors [107]. A gesture spotting device using only two wrist-worn sensors, a 3-axis accelerometer and microphone was designed in [108]. Ultrasonic sensors and magnetometers were used to correct the drift of IMUs using Extended Kalman filter in [109]. Ultrasonic time of flight sensors and inertial measurements were combined using an extended Kalman filter for practical motion capture in everyday surroundings in [110]. An optoacoustic method fusion with IMUs using particle filter was presented in [111] where a median position and orientation error of 26 mm and 10° were obtained. A summary of various sensing methods for human motion capture and gait analysis is listed in Table 2.1

2.3 Signal Design for Ultrasonic Ranging Sensors

Ultrasonic waves can be utilized for accurate small-scale localization. The system becomes cheap and wearable with low power consumption if narrowband piezoelectric sensors are utilized. Such a small scale localization system can be employed for long-term human gait analysis in rehabilitation clinics and unrestrained environments [30]. In [30], single tone pulses were used for tracking a mobile node attached to one of the lower limbs. A frequency-modulated signal such as a linear chirp can provide narrower cross-correlation peak at the receiver side than that obtained by a single frequency burst using correlation receivers [114]. It can also

TABLE 2.1: Various sensing methods for human motion analysis

Sl No.	Method	Accuracy	Advantages	Disadvantages	Ref.
1	Visual based systems with markers	About 1mm	More number of markers	Clutter, Occlusion, changes in lighting	[8, 112]
2	Visual Markerless systems	Few cms	Compact, portable and free from marker artifacts	Occlusion, intensive computation, use of high speed cameras, changes in lighting	[26, 47, 113]
3	Inertial Measurement Units	Few cms	Portable, low cost, compact, and not limited by capture volume	Drift, fluctuating offsets and requirement of other sensors to correct drift	[19, 58]
4	Magnetic sensors	Depends on number of sensors and magnetic disturbances	Compact, low cost and portable	Interaction with ferromagnetic materials	[59, 61]
5	Wearable force and pressure sensors	No 3D Tracking	Can be used in unrestrained environments	Mechanical failure, data recorded only during stance phase	[63, 64]
6	Sensor fusion	High	Improved accuracy and performance	Increased complexity and cost, synchronization overheads	[25, 103, 104]
7	Robotic	High	Less chances of error	Limits movement and less compact	[71, 72]
8	Ultra wideband	Sub centimeter with accurate clock synchronization	Low power consumption, robust performance in multipath environments	Difficult to get accurate clock synchronization, ADCs with high sampling rates are required	[27, 74]
9	Ultrasound	Less than 1cm with modulation	Low cost, portable and customizable	Occlusion, slow update and echo	[22, 49, 86]

enable the system for scaling up the number of mobile nodes that can be tracked simultaneously by exploiting various modulation techniques such as Orthogonal Frequency Division Multiplexing (OFDM) [86] or other chirp diversity multiple access methods [115]. Orthogonal Frequency Division Multiplexing (OFDM) was implemented using narrowband ultrasonic sensors in [86]; however, OFDM signals suffer from high peak to average power ratios. Also, the Doppler effect can disturb the orthogonality of the signals involved. Leaving guard bands between different orthogonal carrier frequencies to avoid interference demands more bandwidth. To track more than two mobile nodes, some chirp diversity coding is required so that all transmitters can transmit simultaneously. A wireless portable and economic gait analysis system with only one ultrasonic marker attached to the lower limb was proposed by *Qi et al.* [22]. Here eight pulses of single-tone frequency of 40 kHz were used for ranging. A net RMSE of 42.99 mm in 3D space was obtained compared to optical motion capture system [13]. ToA can be estimated in ranging sensors using different methods such as thresholding, cross-correlation with the originally transmitted signal or by comparing the phase of the received signal with the original. A phase-correlation method to improve the correlation performance was explained in [116], which requires higher SNR levels to provide satisfactory performance. The cross-correlation method is accurate and robust compared to other methods in a noisy environment [117]. As the noise increases, the performance of cross-correlation decreases if single-tone signals are used. The signal design and coding is crucial in these systems for better tracking accuracy and effective utilization of available bandwidth. An interlaced-BPSK was implemented for localization in [79]. Binary phase shift keying (BPSK) was used to code the transmitted signals in [118] to improve the cross-correlation performance. However, the performance degrades in time-varying fading channels [5]. Barker codes were used in [119]. Spread spectrum signals were used along with narrowband ultrasonic sensors in [101]; however, the use of 1 kHz clock for the pseudo-random code increases the length of the transmitted signal which leads to limited data update rate for tracking. Pseudo-random codes were used for ultrasonic channel multiple access [120] with an increased time-bandwidth product using wideband electrostatic transducers. The width of the autocorrelation peak decreases as the time-bandwidth product of the signal increases. Lower width of the auto-correlation peak, in turn, provides better range properties for the signal. A significant improvement in cross-correlation performance can be observed when linear frequency

modulated signals are used [121, 122]. The accuracy of cross-correlation increases with the bandwidth of the chirp signals [116]. Even though broadband ultrasonic sensors provide higher accuracy compared to narrowband ultrasonic sensors, these sensors come at a higher cost and operating voltage. Hence, we use narrowband piezoelectric transducers along with linear chirp signals for ranging in our experiments.

2.4 Bilateral Gait Symmetry and Coordination

Bilateral symmetry refers to the similarity between the left and right part of human body movements. Traumatic unilateral pathology often results in a markedly asymmetric gait [123]. Despite the existence of a small amount of gait asymmetry in healthy adults in terms of spatial and temporal parameters [124], gait may become increasingly asymmetric in the presence of pathology. Previous studies have shown the presence of gait asymmetry in patients with Parkinson's disease, cerebrovascular accidents, and in amputees using prosthesis [125–127]. Bilateral coordination measures estimated during tasks that require a high degree of left-right coordination like turns or step initiation can be used as a tool to predict the freezing of gait in Parkinson's disease [128]. Gait was found to be asymmetric even in some patients with early stages of Parkinson's disease [129]. Symmetry measure along with gait speed can be used for post-stroke assessment of gait [130]. Hence it is essential to analyze the gait symmetry and coordination between the limbs. Evaluation of gait symmetry after stroke was studied in [131]. From the spatiotemporal parameters of gait (say X), the gait symmetry can be quantified by any of the following methods [131]:

- Symmetry ratio(GS): $GS = X_{paretic}/X_{non-paretic}$
- Symmetry index(SI): $SI = [(X_{paretic} - X_{non-paretic}) / 0.5(X_{paretic} + X_{non-paretic})] \times 100\%$
- Gait asymmetry(GA): $GA = |100 \times [\ln(X_{paretic}/X_{non-paretic})]|$
- Symmetry angle(SA): $SA = [(45^\circ - \tan^{-1}(X_{paretic}/X_{non-paretic})) \times 100\%]/90$

Among the above-mentioned symmetry measures, the symmetry ratio(GS) is easier to interpret and is a recommended candidate on the basis of potential clinical

utility [131]. In the end of this thesis, we also derive a bilateral gait deviation measure from the 3D trajectories which takes into account the deviation of left and right lower limbs during the swing phase.

2.5 Measurement of Joint Flexion and Extension Angles

Traditionally, the range of motion of human joint angles has been measured using goniometers in hospitals. Joint angle measurement during various activities was done by a physiotherapist in hospitals and required a great deal of overhead. For remotely measuring joint angles, Motion capture systems have been used to quantify joint kinematics by tracking reflective surface markers [132]. However, these systems are complex, costly, need controlled laboratory settings, susceptible to occlusion, and skin movement artefacts. The advantages of small size and robustness of accelerometers and gyroscopes were utilized in some of the works. Joint angles can be calculated by double integrating the measured angular acceleration or integrating angular velocity [133]; however, integration incurs errors due to pronounced drift. Joint angles can also be calculated by estimation of inclination angles between segments and vertical, followed by subtraction of angles of neighboring body segments. Here, the segment accelerations should be small compared to the gravity [14]. Methods for drift correction during integration were proposed in some of the earlier works; however, most of the works employed additional sensors and complex algorithms or procedures to offset the error accumulation. In [134], the author made the signal at the beginning and end of each walking cycle equal by identifying the beginning and end of each cycle. A low cut high pass filter on the inclination angle signals from shank and thigh were applied in [135]. However, these methods removed the static and low-frequency components of the angle estimation. A comparison of weighted accelerations of joints obtained from two accelerometer pairs mounted on two adjacent segments of the leg was employed to extract the joint angles without integration in [136]. The drawbacks of the system were the delays due to low pass filtering and the difficulty in aligning the accelerometer pairs so that the axes intersect at the joint. IMUs with triaxial accelerometers were used to measure thigh, shank and knee pitch and yaw angles [137, 138]. These studies were limited to two degrees of freedom for limited activities. The majority of

systems using IMUs combined two or more types of sensors to estimate the joint angles [139], which made the system complex. Accelerometers and Magnetometers were used to compensate for the orientation error that occurs during the integration of the angular rate from gyroscopes [140]. All of them were applicable for limited circumstances. Integration drift affects accelerometers and magnetic disturbances from different sources affect magnetometer readings. Hence a low-cost portable system for unobtrusive tracking of joint kinematics is of high importance.

Use of ultrasound for accurate tracking of human limb joint angles during gait was not extensively studied in the literature. A measuring head with three transmitters and triplets of ultrasonic receivers attached to each segment of the body were used for estimation of joint kinematics and parameters of gait in [141]. However, the markers attached to the body were large, and the maximum range of sensors was limited to 3 meters. In this thesis, we also study the methods to track lower limb knee and hip joint angles using a minimum number of wearable nodes attached to the body. A method to evaluate lower limb joint angles during gait with only two wearable mobile nodes and study the effect of noise on the tracking performance is described.

To conclude, we have discussed different kinds of sensors for ranging, localization and human motion tracking. The advantages and disadvantages of different systems are also examined and we observe that wearable wireless sensor nodes such as UWB and ultrasonic sensor systems can provide high 3D tracking accuracy with reduced cost and complexity. In the next chapter, we discuss the design of wearable wireless sensor nodes and compare the localization performance of UWB and ultrasonic systems.

Chapter 3

Methods for Positioning, System design, and Sensor selection

In this chapter, some methods used for ranging, localization, and gait phase segmentation are explained. These methods are used in the remaining chapters to obtain 3D coordinates from the ranging data and to obtain the spatial and temporal parameters from the 3D coordinates. The second part of the chapter provides a comparative study of UWB and ultrasonic sensors for gait analysis and selects the best option for further analysis.

3.1 Narrowband Sensors for Ultrasonic Ranging

We used narrowband sensors MA40S4S and MA40S4R by Murata in our experiments with ultrasonic signals except in Chapter 6, where SRF02 (Devantech, UK) ultrasonic sensors are used. We used SRF02 sensors in Chapter 6 as the sensors come with a small footprint printed circuit board which can be made to transmit 40kHz monotonous pulses for ranging. We don't need to alter the transmission signals for the experiments in Chapter 6. Even though we used a different sensor, both MA40S4S and SRF02 sensors have similar properties. Figure 3.1 shows the frequency characteristics of MA40S4S sensor. It can be observed that we can get a sound pressure level greater than 100 dB for around 10 kHz bandwidth. These sensors can be driven by lower voltages ($<20\text{v}$). Narrowband piezoelectric sensors such as MA40S4S are much cheaper and power-efficient compared to broadband

ultrasonic sensors such as electrostatic transducers and piezo film transducers such as EMFi and PVDF, where a high polarization voltage needs to be applied [37]. Piezoelectric sensors provide higher sound pressure level with lower voltage, thus making it a good choice for wearable and battery-operated applications.

Narrowband ultrasonic sensors with a single mobile node were employed for human motion capture in [13]. However, we need some signal encoding techniques to enable channel multiple access for simultaneous transmission without cross-talk and without affecting the data update rate. There are two main constraints in encoding ultrasonic waves: directivity and low bandwidth [142]. We selected narrowband chirp signals to utilize the available bandwidth of these sensors effectively.

FIGURE 3.1: Frequency characteristics of MA40S4S [1]

3.2 Ranging

Ranging is the first step in range-based localization systems. Estimation of the distance between two points in space by sending a signal from the transmitter to the receiver is called ranging [143]. Different methods for ranging between two wireless nodes include RSSI, one-way ToA, two-way ToA, double sided ToA, etc. Let $S(t)$ be the signal which is transmitted from the transmitter, the corresponding

received signal can be represented as:

$$R(t) = h(t) * S(t) + n(t) \quad (3.1)$$

where the channel impulse response is $h(t)$ and $n(t)$ is the channel noise. For ideal channel without multi-path or multiple access interference, the Equation (3.1) can be written as:

$$R(t) = A_r \times S(t - \tau) + n(t) \quad (3.2)$$

where A_r represents the received signal strength and τ represents the time delay. We will be using time-delay based ranging methods as they can provide better range information than RSSI methods.

3.3 Peak to Average Power Ratio

Ranging in wireless sensors requires a signal to be sent from a transmitter to a receiver to measure the distance. Peak to Average Power Ratio (PAPR) is defined as the ratio of peak power to the average power of a signal which is transmitted from one node. Efficient ranging requires the PAPR of the signals to be low. A major disadvantage of the multi-carrier transmission or OFDM is the high PAPR [144]. A multi-carrier signal can be defined as the sum of independent signals modulated onto sub-channels of equal bandwidth. Let $x(t)$ be the complex envelope of the transmitted signal in the time domain, then the PAPR of the signal can be expressed as:

$$PAPR = \frac{\max_t [|x(t)|^2]}{E(|x(t)|^2)} \quad (3.3)$$

where $E(|x(t)|^2)$ is the average power of $x(t)$. We are employing chirp signals in our methods as they can provide lower PAPR compared to multicarrier signals.

3.4 Localization

Two main ToF-based localization techniques in wireless sensor networks are spherical and hyperbolic positioning. Spherical positioning is efficient if the range estimations are error-free [13].

3.4.1 Spherical Positioning

Consider N anchor nodes (or reference nodes) with known positions and M mobile nodes in a 3D space. The distance from one mobile node, m to each anchor node defines a sphere centered at the anchor node and with a radius equal to the distance. The position of a mobile node is given by the point of intersection of all the spheres defined by it with each anchor node. This positioning method can be employed when a common clock is available between the mobile nodes and anchor nodes, or some methods are employed for removing clock offsets and drifts. At least four anchor nodes are required to obtain the 3D coordinates of one mobile node. The intersection between N spheres can be computed for localization of i^{th} mobile node by solving Equation (3.4):

$$\begin{bmatrix} \sqrt{(x_1 - x_i)^2 + (y_1 - y_i)^2 + (z_1 - z_i)^2} \\ \sqrt{(x_2 - x_i)^2 + (y_2 - y_i)^2 + (z_2 - z_i)^2} \\ \vdots \\ \sqrt{(x_N - x_i)^2 + (y_N - y_i)^2 + (z_N - z_i)^2} \end{bmatrix} = \begin{bmatrix} d_{1,i} \\ d_{2,i} \\ \vdots \\ d_{N,i} \end{bmatrix} \quad (3.4)$$

where (x_i, y_i, z_i) are the coordinates of mobile node to be estimated, $(x_{1..N}, y_{1..N}, z_{1..N})$ represent the coordinates of anchor nodes and $d_{1..N,i}$ represent the measured distances for i^{th} anchor node.

3.4.2 Hyperbolic Positioning

Hyperbolic positioning employs relative range measurement to determine the location of the target as it requires only receivers synchronized, but it demands high accuracy synchronization for short-range localization [41]. The difference in times of arrival is used for locating the mobile node. The coordinates of the mobile node are estimated by finding the intersection of hyperboloids defined by Equation (3.5):

$$\begin{bmatrix} D_{2,i} - D_{1,i} \\ D_{3,i} - D_{2,i} \\ \vdots \\ D_{N,i} - D_{N-1,i} \end{bmatrix} = \begin{bmatrix} d_{2,i} - d_{1,i} \\ d_{3,i} - d_{2,i} \\ \vdots \\ d_{N,i} - d_{N-1,i} \end{bmatrix} \quad (3.5)$$

where $D_{k,i} = \sqrt{(x_k - x_i)^2 + (y_k - y_i)^2 + (z_k - z_i)^2}$ for $k = 1, 2 \dots N$.

3.4.3 Cramer-Rao Lower Bounds for ToA and TDoA

Any localization system will contain a method for measuring range and a positioning method. In the ranging method, there will be errors in the measured range due to clock synchronization problems and transmission delays. In the positioning method, the relation between the 3D position and the measured range values is non-linear. Direct localization of mobile nodes using these non-linear measurement equations gives better tracking performance than linearizing the measurement equation [145]. In estimation theory, non-linear estimation problem of any unbiased estimate is bounded by Cramer-Rao Lower Bound (CRLB). In localization problems, CRLB provides a theoretical lower bound of the variance of the position estimates. It is given by the inverse of fisher information. The performance of ToA is not usually higher than TDoA, and their performances become identical in some highly symmetrical sensor geometries [146]. We consider three locators to find a mobile target in a 2D plane and plot the lower bounds for ToA and TDoA. If C_{xy} represents the covariance matrix of the position estimate $[xy]^T$. Then,

$$C_{xy} \geq Tr[I^{-1}(x, y)] = CRLB \quad (3.6)$$

Where, $I(x, y)$ is the Fisher information matrix. In a planar polar coordinate system, the equations for CRLB for ToA and TDoA can be derived as follows [13, 147]:

$$CRLB_{ToA} = \sigma_0^2 \left[\frac{\sum_1^N C^2\theta_j + \sum_1^N S^2\theta_j}{\sum_1^N C^2\theta_j \times \sum_1^N S^2\theta_j - \sum_1^N C^2\theta_j S^2\theta_j} \right] \quad (3.7)$$

$$CRLB_{TDoA} = 2\sigma_0^2 \left[\frac{\sum_2^N (C\theta_j - C\theta_1)^2 + \sum_2^N (S\theta_j - S\theta_1)^2}{\sum_2^N (C\theta_j - C\theta_1)^2 \times \sum_2^N (S\theta_j - S\theta_1)^2 - \sum_2^N (C\theta_j - C\theta_1)^2 (S\theta_j - S\theta_1)^2} \right] \quad (3.8)$$

Where, C and S represent Cos and Sin respectively. We considered polar coordinate system with $(x_j, y_j) = (d_j Cos\theta_j, d_j Sin\theta_j)$ for $j = 1, 2 \dots N$. N is the number of anchor nodes. The effect of pathloss on error was also neglected. The plot of CRLB for both the methods when the four anchor nodes are located (in meters)

FIGURE 3.2: The graph representing the Cramer-Rao lower bounds for ToA and TDoA for positioning a mobile node using four anchor nodes in a plane.

at $(0,1)$, $(-1,0)$, $(1,0)$, and $(0,-1)$ are shown in Figure 3.2. It can be observed that the lower bound for ToA is lower than TDoA. Hence, we select ToA with clock synchronization for spherical positioning in our project [146, 148].

In practice, range estimations are prone to various kinds of errors and we use an Unscented Kalman Filter (UKF) [149] to get a reasonable estimate of the 3D position from the range estimates.

3.4.4 System Modeling

In our system, spherical positioning with four anchor nodes is employed. The distance from mobile nodes to each anchor node is estimated. A UKF was used along with a smoothing filter to estimate the three-dimensional coordinates of a mobile node from four distance measurements. In UKF, unscented transformations are used where mean and covariance of the target distribution are approximated directly instead of trying to approximate the non-linear function [149].

$$\begin{aligned}\mathbf{x}_k &= \mathbf{A}\mathbf{x}_{k-1} + \mathbf{q}_{k-1} \\ \mathbf{y}_k &= \mathbf{g}(\mathbf{x}_k) + \mathbf{r}_k\end{aligned}\tag{3.9}$$

where $\mathbf{x}_k$ denotes the state of the system and $\mathbf{y}_k$ denotes the measured distances at the instant k , $\mathbf{A}$, $\mathbf{g}(\mathbf{x}_k)$, $\mathbf{q}_k$ and $\mathbf{r}_k$ are the state transition matrix, matrix of

measured distances, process noise, and the measurement noise respectively. The state of the system at the instant k is given as:

$$\mathbf{x}_k = \begin{bmatrix} x & y & z & \dot{x} & \dot{y} & \dot{z} \end{bmatrix}^T \quad (3.10)$$

where x, y and z are the Cartesian coordinates of the mobile node to be tracked and $\dot{x}, \dot{y}$ and $\dot{z}$ are the corresponding velocities. The state transition matrix is given by Equation (3.11).

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & 0 & T & 0 & 0 \\ 0 & 1 & 0 & 0 & T & 0 \\ 0 & 0 & 1 & 0 & 0 & T \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (3.11)$$

where T is the sampling time. $\mathbf{q}_{k-1} \sim N(0, Q_{k-1})$ where Q_{k-1} is the process noise covariance matrix.

$$\mathbf{Q}_{k-1} = \begin{bmatrix} \frac{T^3}{3}q_x^2 & 0 & 0 & \frac{T^2}{2}q_x^2 & 0 & 0 \\ 0 & \frac{T^3}{3}q_y^2 & 0 & 0 & \frac{T^2}{2}q_y^2 & 0 \\ 0 & 0 & \frac{T^3}{3}q_z^2 & 0 & 0 & \frac{T^2}{2}q_z^2 \\ \frac{T^2}{2}q_x^2 & 0 & 0 & Tq_x^2 & 0 & 0 \\ 0 & \frac{T^2}{2}q_y^2 & 0 & 0 & Tq_y^2 & 0 \\ 0 & 0 & \frac{T^2}{2}q_z^2 & 0 & 0 & Tq_z^2 \end{bmatrix} \quad (3.12)$$

where q_x, q_y and q_z can be approximated as the standard deviations of velocity noise along x, y, and z directions.

$$\mathbf{g}_i(\mathbf{x}_k) = \sqrt{(x_k - x_i)^2 + (y_k - y_i)^2 + (z_k - z_i)^2} \quad (3.13)$$

where x_i, y_i and z_i represents the coordinates of the fixed anchor nodes. $\mathbf{r}_i \sim N(0, R_i)$ where R_i is the measurement noise covariance matrix. R_i can be approximated as a diagonal matrix with constant diagonal elements as the noise in each sensor measurement which can be approximated as independent. $R_i = \text{diag}(e^2, e^2, e^2, e^2)$ where e can be estimated as the standard deviation of ultrasonic

measurements. The values of q_x, q_y and q_z were empirically found by minimizing the RMSE between the ultrasonic and camera data. An Unscented Rauch-Tung Striebel smoother was also used to smooth out the waveform [150].

3.4.5 Kalman Filter

A UKF was designed for estimation of 3D coordinates of the mobile nodes along with the non-linear state space model described in the previous section. The algorithm used the following steps [151]:

(A) Prediction step

- Generate $(2n + 1)$ matrix of sigma points (χ) and associated weights (W) for unscented transformation.

$$\begin{aligned}\chi_{k-1} &= [m_{k-1} \quad \dots \quad m_{k-1}] + \sqrt{n + \lambda} [0 \quad \sqrt{P_{k-1}} \quad -\sqrt{P_{k-1}}] \\ W_0^{mean} &= \frac{\lambda}{n + \lambda}, \quad W_0^{cov} = W_0^{mean} + (1 - \alpha^2 + \beta) \\ W_i^{mean} &= W_i^{cov} = \frac{1}{2(n + \lambda)} \quad \text{for } i = 1, \dots, 2n\end{aligned}\tag{3.14}$$

where, λ is a scaling parameter given by $\lambda = \alpha^2(n + r) - n$, α , β , and r are constants.

- Propagate the sigma points through the state space dynamic model.

$$\hat{\chi}_{k,i} = f(\chi_{k-1,i}) \quad i = 1 \dots 2n + 1\tag{3.15}$$

- Predict the mean state matrix m_k^- and covariance matrix P_k^- .

$$\begin{aligned}m_k^- &= \sum_i W_{i-1}^{mean} \hat{\chi}_{k,i} \\ P_k^- &= \sum_i W_{i-1}^{cov} (\hat{\chi}_{k,i} - m_k^-)(\hat{\chi}_{k,i} - m_k^-)^T + Q_{k-1}\end{aligned}\tag{3.16}$$

(B) Update step

- Generate the matrix of sigma points.

$$\chi_k^- = [m_k^- \quad \dots \quad m_k^-] + \sqrt{n + \lambda} [0 \quad \sqrt{P_k^-} \quad -\sqrt{P_k^-}]\tag{3.17}$$

- Propagate the sigma points through the measurement dynamic model.

$$\hat{Y}_{k,i} = g(\chi_{k,i}^-) \quad (3.18)$$

- Compute the mean (μ_k), covariance of the measurement (S_k) and cross covariance of the state and measurement (C_k).

$$\begin{aligned} \mu_k &= \sum_i W_i^{mean} \hat{Y}_{k,i} \\ S_k &= \sum_i W_i^{cov} (\hat{Y}_{k,i} - \mu_k)(\hat{Y}_{k,i} - \mu_k)^T + R_k \\ C_k &= \sum_i W_i^{cov} (\chi_{k,i}^- - m_k^-)(\hat{Y}_{k,i} - \mu_k)^T \end{aligned} \quad (3.19)$$

- Compute the Kalman gain K , state mean m_k , and covariance P_k after obtaining measurement update y_k and update mean state and covariance.

$$\begin{aligned} K &= C_k S_k^{-1} \\ m_k &= m_k^- + K(y_k - \mu_k) \\ P_k &= P_k^- - K S_k K^T \end{aligned} \quad (3.20)$$

3.4.6 Unscented Rauch-Tung Striebel Smoother

Smoothing refers to Bayesian statistical methodology that can be used for computing estimates of past state history of a time-varying system based on the history of obtained noisy measurements [150]. An additive form of Unscented Rauch-Tung Striebel smoother was implemented. The recursive algorithm starts from the last step and proceeds backward. The procedure for computing smoothing distribution of step k from that of step $k+1$ is explained here.

- Calculate the matrix of sigma points.

$$\chi_k = [m_k \quad \dots \quad m_k] + \sqrt{(n + \lambda)} [0 \quad \sqrt{P_k} \quad -\sqrt{P_k}] \quad (3.21)$$

- Propagate sigma points through the state space dynamic model.

$$\hat{\chi}_{k+1,i} = f(\chi_{k,i}), \quad i = 1, \dots, 2n + 1 \quad (3.22)$$

- Predict the mean m_{k+1}^- , covariance P_{k+1}^- and cross-covariance C_{k+1} .

$$\begin{aligned}
m_{k+1}^- &= \sum_i W_{i-1}^{mean} \hat{\chi}_{k+1,i} \\
P_{k+1}^- &= \sum_i W_{i-1}^{cov} (\hat{\chi}_{k+1,i} - m_{k+1}^-)(\hat{\chi}_{k+1,i} - m_{k+1}^-)^T + Q_k \\
C_{k+1} &= \sum_i W_{i-1}^{cov} (\chi_{k,i} - m_k)(\hat{\chi}_{k+1,i} - m_{k+1}^-)^T
\end{aligned} \tag{3.23}$$

- Compute the smoother gain SG_k and final smoothed mean m_k^s and covariance P_k^s .

$$\begin{aligned}
SG_k &= C_{k+1}[P_{k+1}^-]^{-1} \\
m_k^s &= m_k + SG_k(m_{k+1}^s - m_{k+1}^-) \\
P_k^s &= P_k + SG_k(P_{k+1}^s - P_{k+1}^-)SG_k^T
\end{aligned} \tag{3.24}$$

where SG_k is the smoother gain, m_k^s and P_k^s are smoothed mean and covariance respectively.

The smoothing and filtering distribution of the last time step are the same. So $m_T^s = m_T$ and $P_T^s = P_T$

3.5 Phases of Gait and Estimation of Gait Parameters

There are two main phases of human gait, the swing phase, and the stance phase. Swing phase starts at the instance when one foot leaves the ground(toe-off) and ends at the instance when the same foot touches the ground(heel-strike). For a normal gait, the swing phase spans 40 percent of the total gait cycle, and stance phase spans the remaining 60 percent. Accurate detection of gait phases is crucial in gait analysis to interpret kinetic and kinematic data [152]. Wavelet transformation can be used for gait events detection from various kinds of sensors as it can detect a specified frequency at a specified time interval. Wavelet transformation of gyroscope data was employed to extract the temporal parameters of gait in [153]. Six states of the art accelerometer-based gait event detection algorithms were tested in real-world scenarios using healthy subjects in [154], and the results show that the

performance of all algorithms degraded in more dynamic conditions with varying gait speeds and changing surface inclinations while all algorithms performed well in controlled indoor environments. However, spatial parameters cannot be extracted with high accuracy from inertial measurement units.

A typical gait cycle showing gait phase segmentation for right leg is shown in Figure 3.3. Heel-strike and toe-off events separate swing phase and stance. Detection

FIGURE 3.3: Phases of Gait: The stance phase of right leg starts at the heel-strike (HS) and ends at the toe-off (TO). Swing phase starts when toe leaves the ground and ends just before HS. Double-Support is the phase when both legs touch the ground [2].

of heel-strike and toe-off helps to segment the continuous gait data into swing and stance phases. The method for finding the gait parameters, heel-strike, and toe-off events from the 3D trajectory of lower limbs during treadmill walk is explained here. The coordinate axes were defined as shown in Figure 3.4 with walking direction as the +X axis.

FIGURE 3.4: Coordinate system for gait parameters estimation during treadmill walk [2].

3.5.1 Detection of Heel-Strike and Toe-Off

Heel-strike (HS) and Toe-off (TO) can be detected as the maximum and minimum points on the x-coordinate of the foot trajectory.

$$\begin{aligned} HS(i) &= Time(max(x(i))) \\ TO(i) &= Time(min(x(i))) \end{aligned} \quad (3.25)$$

3.5.2 Estimation of Spatial and Temporal Parameters of Gait from 3D Coordinates of Lower limbs

We estimate the spatial and temporal gait parameters from the 3D coordinates of one lower limb. The estimation of some gait parameters from the X and Z coordinates of a single gait cycle is as shown in the Figure 3.5. The peaks in the x-coordinate can be assumed as the heel-strikes, and the troughs in the x-coordinate can be assumed as the toe-off points [13].

FIGURE 3.5: Estimation of gait parameters from a single gait cycle.

- *Swing Phase and Swing Time (SWT)*: Swing time is defined as the time taken for completing one swing phase. Swing phase of one foot starts from the toe-off of the current step to the heel-strike of next step of the same foot. In normal gait, swing phase occupies 40% of the time. The swing time at the i^{th} step is given by [22].

$$SWT(i) = Time(max(x(i))) - Time(min(x(i)))$$

- *Stance Phase and Stance Time (STT)*: Stance phase starts at the heel-strike and ends at the toe-off. Time taken from the heel-strike to next toe-off of the same foot is defined as stance time. The stance time at the i^{th} step is given by

$$STT(i) = CycleTime - SWT(i)$$

$$STT(i) = Time(min(x(i+1))) - Time(max(x(i)))$$

Where *CycleTime* is the time taken to complete a stride which is the time between successive heel-strikes of the same foot.

- *Stride Time (ST)/Cycle Time*: Stride Time is defined as the time taken from one heel-strike to the next heel-strike of the same foot and is given by the time between two minimum points of the x-coordinate.

$$ST(i) = Time(min(x(i+1))) - Time(min(x(i))) \quad (3.26)$$

- *Step Length (S) and Stride Length (SL)*: Stride length is defined as the distance between successive heel-strikes of the same foot. It consists of two step lengths, left and right. It can be estimated as twice the difference between the maximum and the minimum point of x-coordinate.

$$S(i) = max(x(i)) - min(x(i)) \quad (3.27)$$

$$SL(i) = 2 \times S(i)$$

- *Step Width (SW)*: Step width is defined as the lateral distance between the mid-line of the heel-strike of the right and left foot (Figure 3.6). Step width was found to be a factor affecting knee adduction moment during level walking, stair ascent, and descent [155]. An increase in step width will cause a reduction in internal abduction moments [156]. Hence analyzing step width is important in rehabilitation. The step width at the i^{th} step is obtained by taking the difference in z-coordinates of the right and left leg during successive heel-strikes and subtracting one heel width if sensors are attached on the outer edge of the heel. Step width is given by,

$$SW(i) = y(Time(max(x_l(i)))) - y(Time(max(x_r(i)))) - hw \quad (3.28)$$

FIGURE 3.6: Step width: Lateral distance between the heel placements.

where $x_r(i)$ and $x_l(i)$ are the x-coordinates of the right and the left legs respectively and hw is the approximate heel width of a leg which was measured for each subject during the experiment. The subtraction of heel width is not required if sensors are attached at the back of the heel.

- *Maximum Foot Clearance (MFC)*: The foot elevation during swing phase is termed as foot clearance. Maximum foot clearance is the difference between the maximum and the minimum points of z-coordinate during one cycle.

$$MFC(i) = \max_i(z) - \min_i(z) \quad (3.29)$$

- *Stride Velocity (V)*: Stride Velocity is defined as the average velocity of the lower limb during one stride.

$$V(i) = SL(i)/ST(i) \quad (3.30)$$

3.6 The Reference System

We conducted all the experiments in Motion analysis laboratory (Motion Analysis Eagle system, Santa Rosa, CA, USA), School of Mechanical and Aerospace Engineering at Nanyang Technological University (NTU), Singapore. Six high-speed Eagle digital cameras along with the cortex software were used to track the 3-D motion and to benchmark the proposed systems. The motion analysis system was calibrated for the static condition using 4-point L-frame and dynamic condition using 3-point T-wand. The tracking accuracy of the reference system after calibration was found to be (0.35 ± 0.18) mm (Mean $\pm$ Standard deviation). The sampling rate of the reference system was 120 Hz.

3.7 Statistical Analysis and Clinical Validity

3D gait analysis system can tolerate clinically acceptable errors. However, the definition of what measurement error is acceptable depends on the parameter to be measured and the application of the system [157]. For example, the difference of mean step lengths extracted from post-stroke and control subjects were found to be about 82.3mm(15.17%) and 88.8mm(16.61%) for right and left legs respectively in a previous study [158]. Thus a system with sensitivity more than this cannot be used for gait analysis of stroke patients. In this study, we are comparing our measurement results with a motion capture system with sub-millimeter accuracy. The 3D coordinates were compared using RMSE or Pearson's Correlation Coefficient (PCC). The measurements and errors were expressed as the mean and standard deviation and a Wilcoxon rank sum test was conducted for comparing the gait parameters estimated from proposed and the reference systems after removing any constant bias.

3.8 Comparison of Wireless Ultrawideband Sensors with Ultrasonic Sensors for Gait Analysis

In this section, some preliminary experiments are presented to identify the best sensors for ToF measurement and gait analysis. A simple wearable sensor system with only one wearable UWB mobile node to track the 3D trajectory of human gait in unrestrained environments is presented and compared with the tracking performance of ultrasonic sensors for similar applications. Our work focuses on a ToF-based ranging and localization systems as they can be used as a means to track 3D coordinates accurately with respect to a fixed reference frame. UWB waves [159] or ultrasonic waves [22] can be exploited for localization in wearable wireless sensor networks for ranging. The major advantages of UWB-based systems over ultrasound are high data rate, higher penetration power, higher transmission angle and higher range [76]. We design a portable, cost-effective wireless motion tracking system which does not require complex calibration or wired connections between the mobile node and anchor nodes. We studied 3D localization with UWB

sensors for cost-effective gait analysis with four fixed anchor nodes to track one mobile node. A similar system with an ultrasonic sensor attached to a lower limb and four fixed anchors at known positions was used for gait analysis in [28]. Broadband ultrasonic sensors are costly and need high voltages to operate [82]. Even though ultrasonic sensors provide good accuracy, there are no commercially available omnidirectional sensors with a high range which can operate with low voltage batteries so that gait analysis can be conducted for level ground walking for longer distances. We compare UWB sensors to ultrasonic due to their ability to provide a high range (200-300m) compared to ultrasonic sensors and hence, the system can have a large capture volume. With a large capture volume, the sensor system can be used for tracking gait in natural environments or level walking. The main factors affecting the accuracy of UWB ranging are errors in clock synchronization between nodes and the high sampling rate required by the analog to digital converters [28]. Here, we use asymmetric double-sided two way ranging [160] for ranging with Decawave's DW1000 IC, which can give high accuracy in LOS conditions without any wired connections.

3.8.1 Experimental System Setup and Configuration

We employed a UWB Sensor Network to estimate the 3D position coordinates of the lower limb. The UWB mobile node was attached to the backside of the right foot just above the ankle joint. The ToA of the UWB pulses to a set of four anchor nodes were calculated. Double-sided TWR [160] was implemented to synchronize the mobile node and four anchor nodes. Decawave DWM1000 wireless transceiver module (IEEE802.15.4-2011 UWB compliant) which uses Decawave's DW1000 IC was employed along with STM32F072 ARM Cortex M0 processor to design wireless nodes in the system. DW1000 provides precise ranging, LOS and NLOS communication range of up to 290m, high data rate up to 6.8 Mbit/s and low power consumption. It uses the frequency band from 3.5—6.5 GHz. Each node costs about US \$100, and hence the total cost of the system was about US \$500—600, making the system cost-effective compared to optical systems. In this application, we consider only the LOS condition. Each ranging takes about 4—5ms; hence the total update rate for four anchors and one mobile node was found to be greater than 50Hz. Even though the optimal positions of anchor nodes for tracking a mobile node are the corners of a tetrahedron [75], we attached the anchor nodes

FIGURE 3.7: Sensors used:(a) The experimental setup for UWB sensors with four anchor nodes attached on a vertical board at the corners of a $0.5\text{m} \times 0.5\text{m}$ square, (b) UWB antenna attached to the right foot of the subject along with the camera markers [3].

at the corners of a $0.5\text{m} \times 0.5\text{m}$ square on a vertical board as this configuration is easy to set up and makes the system convenient and portable. We will compare the performance with a similar ultrasonic system later. The configuration of the anchor nodes is as shown in Figure 3.7. A 5V power supply powered each anchor node. A mobile node was attached to the right foot as shown in Figure 3.7 with the antenna facing backward, and a 5V lightweight lithium polymer battery powered this mobile node. The vertical board with anchor nodes is placed at the backside of the subject walking on a treadmill. Such a configuration was selected since it can provide high accuracy along the axis perpendicular to the plane of anchor nodes, and the gait movement mainly occurs along this direction. For ranging between the mobile node and each anchor node, double-sided TWR was used, and the measured readings were sent to a PC from mobile node using a CC2530 wireless module from Texas Instruments. The data were processed in Matlab after the acquisition.

3.8.2 Double Sided Two-Way Ranging

Double-sided TWR is explained in Figure 3.8. This method removes the error caused by the clock offset between the crystal oscillators of both sensor nodes. The time of flight between the nodes is calculated by Equation (3.31), where, T_{Round1} and T_{Round2} represents the time delay to get a response from node-2 after sending a signal from node-1 and vice versa. T_{Reply1} and T_{Reply2} are the turn around time

FIGURE 3.8: Schematic representing SDS-TWR for ranging between Node-1 and Node-2 [3]

for node-1 and node-2 respectively.

$$T = \frac{T_{Round1} \times T_{Round2} - T_{Reply1} \times T_{Reply2}}{T_{Round1} + T_{Round2} + T_{Reply1} + T_{Reply2}} \quad (3.31)$$

The discrete state space equation to estimate the 3D coordinates of one mobile node from four distance measurements and UKF are as explained in Section 3.4.4.

3.8.3 Experiment Methods and Data Analysis

Five healthy subjects (4 Males and 1 Female) with age (25.4 ± 0.89) years were recruited for experimental validation of the setup. All the subjects involved did not have any history of severe injury or other diseases which affect gait. All subjects gave their informed consents to participate in the gait experiments. UWB sensors and reference markers of camera system were attached to the right foot of the subject with Velcro tape just above the ankle joint facing backward. The UWB ranging system was calibrated with the reference system before doing experiments. We attached two markers on either side of the antenna and took the mid-point of the line joining them as the reference target to avoid the interference of UWB signals with the camera markers. One camera marker was attached at each anchor node in an initial static calibration so that the relative position of UWB anchor nodes are available in the camera-based coordinate system. After calibration, each subject carried out three treadmill walks at fixed walking speeds of 1, 2 and 3 kph for one minute each. Both systems were started at the same time and the time

shifts between the two systems were adjusted by maximizing the cross-correlation between the signals in the post-processing. The effective data update rate of UWB system was found to be about 50Hz. Cubic spline interpolation was used to match the sampling rate of the system with the camera system which is 120 Hz. The RMSE between the signals from the motion capture system and the UWB system along each axis was calculated separately.

3.8.4 Results from UWB-based Gait Analysis System

The 3-D trajectory of the right lower limb was extracted from each subject using the proposed system and compared to that of the motion capture system. The plots of data obtained from the proposed system and the motion capture system for x,y, and z coordinates are provided in Figure 3.9 and the RMSE calculated along each direction from the collected data is given in Table 3.1. The data show that the accuracy along X(horizontal) direction is high enough to extract spatiotemporal parameters. The mean RMSE along X direction was found to be 19, 20.83 and 23.14mm for walking speeds 1, 2 and 3 kph respectively. The average value of PCC obtained for the X-coordinate was found to be 0.992. However, the accuracies along the Y and Z directions were found to be lesser compared to the X direction. This might be due to dilution of precision [86] and lower ranging accuracy due to multi-path reflections from the ground or the treadmill as the distance between anchor nodes are lesser compared to the distance between the mobile node and anchor nodes. It is also affected by the Doppler effect; however, the effects of Doppler effect will be very less at walking velocities for UWB signals. Due to the relative velocity of transmitter and receiver, there are three sources of errors introduced in the system [161]: (1) Doppler shift, (2) change in relative location while the packet is being received, and (3) change in channel impulse response while the packet is being received. The Doppler shift and change in channel impulse response will be compensated by timing recovery circuit in the module at walking velocities in the absence of the multi-path effect. The change in relative location can be avoided by using a lower packet size. However, the presence of multi-path along with Doppler effect degrade the performance of the system. The RMSE was found to be less dependent on walking speed. Table 3.2 shows the mean and standard deviation of the gait parameters estimated from both systems at walking speed of 3 kph. The mean error and standard deviation of the error in estimating step

length, swing time, and stride time are listed in Table 3.3. Figure 3.10 shows the Bland-Altman plots with mean and difference between the parameters(stride length and stride time) extracted from the UWB system and the motion capture system for one subject walking at 3 kph. The upper and lower limits of agreement were mean difference $\pm 2 \times$ standard deviation of the difference as shown in the Figure 3.10. The plots show an agreement between both systems with 95% limits of agreement $[-21.06, 26.62]$ mm and $[-63.50, -13.10]$ ms for step length and swing time respectively. The average stride velocity over one stride can be estimated by dividing the stride length by stride time. The results of error between the stride velocity estimated from the proposed system and the reference system are as shown in Table 3.4.

The main limitation of the system is the lower accuracy along X and Z directions.

TABLE 3.1: RMSE between ultrawideband and camera data in millimeters

Subject	Axis	1 kph	2 kph	3 kph
1	Y	136.37	102.04	109.89
	X	23.56	18.43	18.93
	Z	54.99	44.95	58.03
2	Y	55.42	61.69	71.76
	X	22.43	29.41	35.10
	Z	55.23	54.48	53.80
3	Y	30.79	34.16	35.46
	X	13.39	14.27	16.68
	Z	67.58	76.45	65.61
4	Y	51.05	45.25	32.95
	X	14.41	16.77	16.64
	Z	72.70	61.79	48.17
5	Y	38.65	46.27	88.14
	X	21.25	25.31	28.37
	Z	73.99	70.33	89.83

TABLE 3.2: Mean and Standard deviation of gait parameters estimated for each subject at a walking speed of 3 kph

Subject		Step Length(mm)		Swing Time(ms)		Stride Time(ms)	
		Mean	SD	Mean	SD	Mean	SD
1	UWB	511.79	85.18	567.8	16.3	1385	82.2
	Camera	519.12	58.15	548.9	15.4	1384.4	76.5
2	UWB	524.02	26.85	519.8	19	1214.5	34.2
	Camera	467.62	16.78	471.1	12.6	1214.1	32.5
3	UWB	463.23	29.47	458.7	14.2	1158	41.3
	Camera	466.01	24.58	420.4	13	1158	39.9
4	UWB	389.16	60.52	482.5	20.2	1153.3	57
	Camera	427.34	49.1	471.7	18.9	1151.7	52.7
5	UWB	428.42	61.7	492.1	25.2	1121	40.2
	Camera	503.16	67.42	430.3	10.8	1121.5	32.2

FIGURE 3.9: The comparison of graphs from UWB system and Camera system at walking speed of 1 kph. X axis represents lateral displacement, Y represents horizontal displacement and Z represents vertical displacement

FIGURE 3.10: Bland-Altman plots comparing (a) step lengths and (b) swing times calculated from the proposed system with the motion capture system at 3 kph walking speed for one subject. The upper and lower limits are set to mean difference $\pm 2 \times$ standard deviation (SD)

3.8.5 Performance Comparison with Ultrasonic Systems

We compare the performance of the developed UWB system with the ultrasonic system proposed in [13]. Initially, the ranging accuracy was studied for wireless UWB sensors between two static nodes with double-sided two way ranging. Ranging experiments with UWB sensors were conducted five times and the mean value

TABLE 3.3: Mean and Standard deviation(SD) of error between the gait parameters estimated from proposed and motion capture system at walking speed of 3 kph. E[SL], E[SWT] and E[ST] represents the error in step length, swing time and stride time respectively

Subject	E[SL](mm)		E[SWT](ms)		E[ST](ms)	
	mean	SD	mean	SD	mean	SD
1	-15.85	26.89	27.5	18.1	0	21.4
2	56.39	16.68	48.6	16.6	0.3	16.2
3	-2.78	11.92	38.3	12.6	0	11.9
4	-38.18	13.96	10.8	8.8	1.7	12.3
5	-74.73	24.95	61.8	24.7	-0.4	31.5

TABLE 3.4: Mean and Standard deviation(SD) of error between the average stride velocity estimated from the UWB system and the motion capture system, $E[v]$ at various walking speeds in millimeters per second

Subject	$E[v]$ at 1 kph		$E[v]$ at 2 kph		$E[v]$ at 3 kph	
	mean	SD	mean	SD	mean	SD
1	-52.86	23.5	-53.27	24.45	-22.66	38.25
2	52.18	23.67	72.44	26.42	92.98	33.05
3	30.5	20.73	19.01	21.81	-4.89	23.73
4	-14.06	22.1	-52.54	26.93	-66.77	24.37
5	-84.66	29.07	-116.79	42.36	-133	44.81

of the standard deviation of measured value was found to be 25.12 mm. The same set of experiments were repeated for static narrowband ultrasonic sensors with wireless clock synchronization and monotonic pulses at 40 kHz. The mean value of standard deviation was found to be 11.22 mm. This shows that the wireless narrowband ultrasonic sensors provide better precision compared to wireless UWB sensors employing two way ranging. Using ultrasonic sensors and a combination of extended Kalman filter and newton Gaussian method, net-RMSE for walking speed of 1, 2 and 3 miles per hour were found to be 41.19, 41.52 and 42.99 mm respectively [13]. In our experiments with UWB sensors and a similar sensor configuration, net-RMSE was found to be 96.38, 90.33, and 97.63 mm at 1, 2, and 3 kph respectively. The RMSE of coordinate along the walking direction was found to be 19, 20.83, and 23.14 mm respectively for walking speeds of 1, 2, and 3 kph. Thus, the system designed with UWB was cost-effective and gave moderate accuracy for gait parameter extraction along the walking direction such as swing time, stride time, and step length. The error in estimated parameters showed high variation among different subjects. It can have a higher capture volume as the range of the sensors are higher. However, due to higher errors in the range measurements, the 3D accuracy was found to be lesser than similar acoustic systems and the gait parameters along x and z directions like step width and foot clearance etc. cannot be estimated with high accuracy. Hence, we can conclude that wearable ultrasonic sensors are a better choice compared to UWB sensors for small scale 3D localization and gait analysis and can provide the required clinical accuracy for tracking as the error values in UWB system were found to be relatively higher compared

to similar ultrasonic gait analysis systems [13, 162]. Having discussed the sensor system design and positioning algorithms, we will be studying the possibilities of wearable ultrasonic gait analysis system using these methods in the succeeding chapters.

Chapter 4

Doppler Correction Methods Using Ultrasonic Chirp Signals

4.1 Introduction

In Chapter 3, we found that the narrowband ultrasonic sensors performed better than UWB sensors in wireless environments; however, Doppler correction, multipath compensation and multiple access for accurately tracking multiple moving markers requires various signal processing techniques to be implemented with the limited bandwidth of the sensors. The distance traveled by the wave can be estimated from time of flight, t by Equation (4.1) [81].

$$\mathbf{d} = (331.5 + 0.6 \times \mathbf{T}) \times \mathbf{t} \quad (4.1)$$

where T represents the room temperature in degree centigrades, $\mathbf{t}$ is the time in seconds and $\mathbf{d}$ is the distance in meters. Various methods can be used to accurately find the time at which the transmitted waves reach the receiver. Some of them are a simple thresholding technique, cross-correlation of the transmitted signal with the received signal and finding the peak, and by measuring the phase shift between transmitted and received signals. The cross-correlation-based method provides accurate results and is the standard method for Time of Flight estimation [117]. Even though the accuracy of the phase shift method is higher than the cross-correlation based method, the maximum range that can be measured with this method alone is limited to one wavelength [163]. A combination of the phase shift

method and the cross-correlation method was explained in [163] to improve the maximum range to about 6 meters. However, the noise in the cross-correlation results should be less than one wavelength, which might not be true in a typical indoor environment. A threshold-based phase-correlation method was explained in [116]; however, this method can only provide improved performance if the signal to noise ratio is high, and there are no multiple access interference. Cross-correlation accuracy improves when the waveform is a frequency modulated one such as a linear chirp [102]. Frequency modulation also aids channel multiple access. In this work, we implement a cross-correlation method with linear chirp waves for ultrasonic ranging. In practice, the transmitted ultrasonic waves can travel by more than one path to reach the receiver in a cluttered environment leading to multi-path interference. An earliest peak search method can remove most of the multi-path components; however, close multi-path components cannot be separated [164].

In this chapter, we discuss two Doppler correction methods with chirp signals in narrowband ultrasonic sensors. Moving sensor nodes emitting ultrasonic waves introduce Doppler shift in the frequency of the received signals. We propose two novel methods for Doppler correction and compare the performance with existing methods. Chirp signals were found to provide better performance compared to other coding techniques in terms of Doppler tolerance and PAPR [115]. OFDM was used for narrowband ultrasonic ranging in [165]. However, it suffers from high PAPR [166]. In ranging systems, it is important to increase the energy and reduce the amplitude peak of the transmitted signal [166]. Even though there are some PAPR reduction methods for OFDM [166], the performance of these methods depends on the duration of the signal [115]. Hence, we are using chirp signals in the proposed methods. Existing Doppler-correction methods include a bank of correlation receivers [167, 168] which is computationally intense as multiple correlation operations need to be conducted to obtain a single measurement. Two Doppler correction methods are explained here: (1) Pilot-carrier based Doppler correction and (2) Range-Doppler coupling neutralization method.

4.2 Doppler Correction Methods

The Equation of an up-chirp signal from the starting frequency f_s to the ending frequency f_e and chirp duration T_s can be given by Equation (4.2).

$$\begin{aligned} S(t) &= \Re\left(\text{rect}\left(\frac{t}{T}\right) e^{2\pi j\left(f_s t + \frac{(f_e - f_s)t^2}{2 \times T_s}\right)}\right) \\ &= \cos\left\{2\pi\left(f_s t + \frac{(f_e - f_s)t^2}{2 \times T_s}\right)\right\} \quad 0 \leq t \leq T_s \end{aligned} \quad (4.2)$$

Let $\hat{S}(t)$ be the Doppler shifted version of the originally transmitted signal, $S(t)$. The received signal, $R(t)$ is given by:

$$R(t) = \hat{S}(t) * h(t) + n(t) \quad (4.3)$$

Where, $h(t)$ is the channel impulse response and $n(t)$ is the channel noise. At the receiver, correlation output can be given by:

$$C(t) = \left[\hat{S}(t) * h(t) + n(t) \right] \star S(t) \quad (4.4)$$

The correlation output at the receiver side provides higher peak amplitude and lower peak width when the correlation operation is performed with the same signal as the received signal. We aim to reduce the difference between $\hat{S}(t)$ and $S(t)$ during correlation. If we can estimate the exact amount of Doppler shift, we can correct the template waveform stored at the receiver side to match the received signal. In the experiments, we used a linear chirp from 35 kHz to 45 kHz of duration 9 ms. Hence, $f_s=35$ kHz, $f_e=45$ kHz and $T_s=9$ ms.

4.2.1 Pilot-carrier Based Doppler Correction

A computationally efficient Doppler shift estimation using OFDM signal for moving mobile node was proposed in [165]. One of the frequency components was chosen as the pilot carrier, and the amplitude of this particular frequency component was increased compared to other components. However, OFDM signals suffer from high PAPR values [169, 170], and hence we implement a similar pilot carrier-based Doppler correction using chirp signals. The method of pilot-carrier generation and Doppler velocity estimation method is explained here: Consider Equation (4.2),

FIGURE 4.1: Representation of (a) Frequency response (F_x) of the signal after adding the pilot-carrier and (b) the corresponding signal in time-domain.

we took $2 \times N$ point discrete Fourier transform of $S(t)$ to get higher resolution in the frequency domain where N is the number of samples in the signal sampled at F_s ($F_s = 500000$ for ranging experiments). In our experiment, we selected the frequency component corresponding to 40 kHz as the pilot carrier and this frequency component was amplified to five times its normal amplitude. Figure 4.1 shows the frequency response of the signal to be transmitted and the corresponding time-domain representation. It can be observed that the introduction of pilot-carrier introduces ripples in the envelope of the time-domain signal and thus slightly increasing the PAPR values. Let $S(t)$ be the chirp signal before amplifying the

pilot-carrier. The signal $S(t)$ in frequency domain can be represented as

$$S(k) = \sum_{t=1}^{2N} S(t) e^{\frac{-2\pi(t-1)(k-1)}{2N}} \quad (4.5)$$

$S(k)$ can be written as:

$$S(k) = S(1) + S(2) + \dots + S(k_p) + \dots + S(2N) \quad (4.6)$$

where k_p is the pilot carrier frequency component. We modify the amplitude of the pilot-carrier by multiplying its amplitude by A_p to get $\hat{S}(k)$

$$\hat{S}(k) = S(1) + S(2) + \dots + A_p \times S(k_p) + \dots + S(2N) \quad (4.7)$$

The time-domain signal after amplifying pilot-carrier can be obtained by taking inverse fourier transform of $\hat{S}(k)$.

$$\hat{S}(t) = \frac{1}{2N} \sum_{k=1}^{2N} \hat{S}(k) e^{\frac{2\pi(t-1)(k-1)}{2N}} \quad (4.8)$$

At the receiver side, the shift in the pilot-carrier is estimated and the frequency shift is converted to the Doppler velocity of the moving target using Equation (4.9)

$$v_d(t) = \frac{-c \times \delta f(t)}{f_p + \delta f(t)} \quad (4.9)$$

Where, velocity away from the fixed anchor node is taken as positive, $\delta f(t)$ is the frequency shift at time t , f_p is the pilot carrier frequency which is 40 kHz in this case and c is the velocity of sound wave. The estimated Doppler velocity was used for correction of the template waveform at the receiver side using Equation (4.10).

$$\hat{S}(t) = \cos \left\{ 2\pi \left(b(t) f_s t + \frac{b(t)^2 (f_e - f_s) t^2}{2 \times T_s} \right) \right\} \quad (4.10)$$

where, $b(t) = \frac{v}{(v+v_d(t-T_s))}$ and $0 \leq t \leq \frac{T_s}{b(t)}$. One ranging cycle in this case spans 20 ms. To avoid large errors, the Doppler velocity was set zero if the estimated Doppler velocity lies outside -3 to 3 m/s.

FIGURE 4.2: Representation of one ranging cycle for Doppler correction using Range-Doppler coupling neutralization method.

4.2.2 Range-Doppler coupling neutralization method

Ranging using linear chirp signals introduces an error in the measured value which is proportional to the velocity of moving target known as range-Doppler coupling [171]. In this case, the range-Doppler coupling property of the linear chirp signals are utilized for Doppler velocity estimation. The range-Doppler coupling error will be positive or negative depending on the chirp direction. Consider the up and down-chirp signals given in Equation (4.11).

$$\begin{aligned} S_u(t) &= \cos\left\{2\pi\left(f_s t + \frac{(f_e - f_s)t^2}{2 \times T_s}\right)\right\} \quad 0 \leq t \leq T_s \\ S_d(t) &= \cos\left\{2\pi\left(f_e t - \frac{(f_e - f_s)t^2}{2 \times T_s}\right)\right\} \quad 0 \leq t \leq T_s \end{aligned} \quad (4.11)$$

Where, f_s and f_e represents the starting and the ending frequencies, which were set as 35 and 45 kHz respectively. One ranging cycle spans a duration of 20 ms which can be with either up-chirp or down-chirp. After each 20 ms duration, we will estimate one data point by using alternate chirp signals from previous and next ranging cycles.. Hence, the data update rate in this case will be same as that of pilot-carrier based Doppler correction (50 Hz). Figure 4.2 represents two consecutive ranging cycles. The data update points are the time at which one range value is estimated and is shown in Figure 4.3. The estimated range using up- and down- chirp signals can be given by Equation (4.12).

$$\begin{aligned} r_1(t) &= r_0(t) + \frac{\dot{r}(t)f_0T_s}{B} \quad \text{for up-chirp} \\ r_2(t) &= r_0(t) - \frac{\dot{r}(t)f_0T_s}{B} \quad \text{for down-chirp} \\ r_0(t) &= \frac{(r_1(t) + r_2(t))}{2} \end{aligned} \quad (4.12)$$

FIGURE 4.3: Representation of data update points in the system.

Where, r_0 represents the actual range, r_1 and r_2 represents the estimated range by sending up- and down-chirp signals, and $\dot{r}$ represents the target velocity in the ranging direction. f_0 is the center frequency, T_s is the signal duration and B is the swept bandwidth of the chirp signal. The mean value of r_1 and r_2 gives an estimate of r_0 .

In each ranging cycle, the estimated Doppler velocity is used to correct the waveform for correlation at the receiver side. The differential Doppler-velocity, $\Delta\dot{r}(t)$ can be calculated by subtracting $r_2(t)$ from $r_1(t)$.

$$\Delta\dot{r}(t) = [r_1(t) - r_2(t)] \frac{B}{2f_0 T_s} \quad (4.13)$$

At any point, $t = r_s$, if the estimated Doppler-velocity is above the maximum set Doppler-velocity, V_{dmax} or below the minimum set Doppler-velocity, V_{dmin} , The Doppler-velocity used for correction in the next step is reset to zero. The template signals for correlation at the receiver are corrected to account for the Doppler effect with the Doppler velocities obtained in the previous step. The new chirp signals are generated using Equation (4.14) [172].

$$\begin{aligned} \hat{S}_u(t) &= \cos\left\{2\pi\left(b(t)f_s t + \frac{b(t)^2(f_e - f_s)t^2}{2 \times T_s}\right)\right\} \\ \hat{S}_d(t) &= \cos\left\{2\pi\left(b(t)f_e t - \frac{b(t)^2(f_e - f_s)t^2}{2 \times T_s}\right)\right\} \end{aligned} \quad (4.14)$$

Where, $b(t) = \frac{v}{(v+v_d(t-T_s))}$ and $0 \leq t \leq \frac{T_s}{b(t)}$. The velocity of sound waves given by $v = 331.5 + 0.6 \times T$, T is the temperature and $v_d(t - T_s)$ is the estimated

FIGURE 4.4: Plot showing the variation of PAPR against the pilot-amplification factor.

Doppler-velocity at time $t - T_s$ and is given by Equation (4.15).

$$v_d(t - T_s) = \sum_{i=0/r_s}^{t-T_s} \Delta \dot{r}(i) \quad (4.15)$$

4.3 Simulation Results

The amplification factor of the pilot-carrier was optimized using simulations. We found PAPR of the time-domain signal as the amplification factor takes integer values from 1 to 10. The width of the auto-correlation peak of the signal can be an indicator for ranging accuracy. A plot of PAPR and the width of the correlation peak against amplification factor is shown in Figure 4.4. It can be observed that both PAPR and the width of correlation peak increases with the amplitude of pilot-carrier. To find the best amplification factor and to study the performance of the proposed methods, we simulated a custom ultrasonic ranging environment in Matlab. We considered four passive anchor nodes with known positions and one active mobile node. The four anchor nodes were placed at the corners of a $1\text{m} \times 1\text{m}$ square. Pilot-carrier at 40 kHz was added to the chirp signal from 35-45 kHz and 9 ms duration as explained in Section 4.2.1. The signal was transmitted from the mobile node and received at all the four receivers. For the simulation, we subjected the channel to AWGN with SNR 0 dB and a multi-path component at random positions each time with reflection coefficient 0.7. We avoided close multi-path components in the simulations by keeping a minimum separation between the LOS and NLOS equal to $\frac{1}{B}$ seconds. The propagation of the ultrasonic signal in

FIGURE 4.5: The simulated velocity of the mobile node.

FIGURE 4.6: Variation of MAE with pilot-carrier amplification factor.

the air was modeled using Equation (4.16).

$$A = A_0 e^{-\gamma \times d} \quad (4.16)$$

Where A , A_0 and d are the amplitude after attenuation, the originally transmitted amplitude and the distance from transmitter respectively. We set the attenuation constant γ to 0.17 Np/m. The simulation was conducted by moving the mobile node to and fro from the receiver plane with linearly increasing and decreasing velocities between -3 and +3 m/s as shown in Figure 4.5. The mean absolute error (MAE) between the estimated distance and the actual distance between the mobile node and each of the anchor nodes was calculated at various pilot-carrier amplification factors. Figure 4.6 shows the variation of MAE with the pilot-carrier amplification factor. It can be observed that the misidentification of the pilot carrier in the received signal caused large errors when the amplification of the pilot carrier was less than five. Hence we selected the amplitude of pilot carrier as five times its original value in the rest of the experiments.

We used the same simulation environment for ranging using the range-Doppler

TABLE 4.1: MAE between the estimated and actual range measurements in millimeters for four different cases during simulation experiments.

Anchor No.	Pilot-carrier	Range-Doppler coupling neutralization	Without Doppler correction	Bank of correlators
1	12.54	0.65	60.3	45.05
2	12.49	0.72	60.27	45.15
3	12.5	0.69	60.27	44.99
4	12.53	0.64	60.29	45.15

coupling neutralization method, as explained in Section 4.2.2. Here, the velocity of the mobile node was considered constant during one ranging cycle of 40 ms. To compare the performance of the proposed method with existing methods of Doppler correction, we considered four different scenarios: (1) Pilot-carrier based Doppler correction with amplification factor five, (2) Doppler correction using range-Doppler coupling neutralization method, (3) Ranging without Doppler correction, (4) A bank of correlation receivers [172] with 40 correlators.

For the bank of correlators, consider the chirp from f_s to f_e and duration T_s . Each correlator is designed with fixed starting frequency, $f_s=35$ kHz and duration, $T_s=9$ ms. The ending frequency, f_e was varied from 43 kHz to 47 kHz in steps of 100 Hz. The correlation with the slope of the received signal matching with the slope of the generated copy of the transmitted pulse provides the highest peak for the correlation peak [172]. MAE obtained from all the four methods are listed in Table 4.1

4.4 Pendulum Experiments

A pendulum experiment was designed to test the simulation results and observations with Murata MA40S4S/R ultrasonic transducers. Initially, experiments were conducted for ranging between one anchor node and one mobile node attached to the pendulum, as shown in Figure 4.7. The pendulum was made to swing almost perpendicular to the receiver plane (Y-axis). For each trial, the pendulum was released from a position approximately 45° angle to the vertical direction. The transmitters and the receiver were connected to NI-USB 6343 Data Acquisition (DAQ) board, which was connected to the PC through USB for post-processing.

FIGURE 4.7: Setup for ranging between moving nodes.

FIGURE 4.8: Setup for localization of mobile node.

FIGURE 4.9: Setup for pendulum experiment.

The DAQ board drove ultrasonic transmitters by a peak to peak voltage of ± 10 V. Optical motion capture system with six high-speed cameras and reflective markers was used as the reference system as explained in Chapter 3. To evaluate the tracking performance, four anchor nodes were used to localize one mobile node attached to the pendulum, as shown in Figure 4.8. The setup used for pendulum experiment is shown in Figure 4.9

4.5 Results and Discussions

The MAE and RMSE were calculated from ten ranging experiments each for all the four methods, and the mean values are listed in Table 4.2. RMSE along each

TABLE 4.2: Mean value of MAE and RMSE calculated during ranging experiments.

	Pilot-carrier	Range-Doppler coupling neutralization	Without Doppler Correction	Bank of correlators
MAE	8.06	3.83	16.93	19.11
RMSE	12.29	4.58	20.97	26.44

coordinate axis and the net-RMSE are calculated using Equation 4.17.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n e_i^2} \quad (4.17)$$

$$net - RMSE = \sqrt{RMSE_x^2 + RMSE_y^2 + RMSE_z^2}$$

where $RMSE_x$, $RMSE_y$ and $RMSE_z$ are the RMSE along X, Y and Z coordinates respectively. It can be observed that the range-Doppler coupling neutralization method gives a higher performance at the same data update rate. Pilot-carrier was found to be better in Doppler shift correction compared to the bank of correlators. The bank of correlators did not improve and instead degraded the ranging performance; this might be due to the variations in the radiation pattern as the angle between the transmitter and the receiver changes.

The MAE and RMSE were calculated from ten localization experiments each for all the four methods and the mean values are listed in Table 4.3. Using the pilot carrier method, the error along Y-direction was found to be much lesser compared to localization without Doppler correction; however, the error along X and Z directions increased slightly. The increased error along X and Z directions is due to the poor Doppler-frequency resolution in the pilot-carrier based method, which results in some granular noise in the measured range values. If we take 5000-point DFT, the frequency resolution will be 25 Hz and which means that there will be an error of ± 25 Hz in the detected Doppler frequency, which can translate to an error of ± 7 mm in the Doppler correction process. This error mainly affects X and Z directions during the positioning phase due to the dilution of precision as the anchor nodes are arranged in a plane. The net-RMSE was found to be better for ranging using the pilot carrier compared with the case without Doppler correction. The error along X and Z directions for the bank of correlators increased considerably compared to the case without Doppler correction.

TABLE 4.3: Mean value of MAE and RMSE calculated during localization experiments.

	Pilot-carrier	Range-Doppler coupling neutralization	Without Doppler Correction	Bank of correlators
MAEx	15.79	5.05	9.05	104.33
MAEy	6.31	4.90	24.22	19.58
MAEz	12.47	8.17	10.21	64.52
RMSEx	19.62	7.01	11.59	128.17
RMSEy	8.34	6.19	29.82	25.20
RMSEz	17.21	10.55	13.74	86.01
net-RMSE	27.43	14.19	34.89	156.49

4.6 Conclusion

To conclude, range-Doppler coupling neutralization method provides better performance in Doppler correction in moving narrowband ultrasonic sensors. Pilot-carrier based method was found to outperform bank of correlators for Doppler-correction. Also, pilot-carrier based method is computationally less complex compared to bank of correlators. The performance of bank of correlators were found to degrade in some cases during pendulum experiments compared to cases with no Doppler correction. We select range-Doppler coupling neutralization method for Doppler compensation in our gait analysis system as they provide better tracking accuracy with limited bandwidth. Considering two transmissions in 40 ms, this method can provide a pulse repetition frequency of 50 Hz in our gait analysis system.

Chapter 5

A Multi-path Compensation Method for Ultrasonic Ranging System for Gait Analysis

5.1 Introduction

In Chapter 4, we discussed various Doppler correction methods and selected range-Doppler coupling neutralization method for our gait analysis system. In this chapter, we address the multi-path problem. When we transmit an ultrasonic pulse in a cluttered environment, the signal can travel in more than one path and the reflections from the ground or nearby objects can add multi-path interference in the received signals. Monotonic ultrasonic sensors were used for tracking lower limbs in [28, 162] where net RMSE for tracking each lower limb was found to be around 30-50 mm. In these methods, multi-path components were removed by keeping an inhibit time after the reception which is not robust in high multi-path environments. In traditional correlation receivers [114], the time at which the peak of the correlation happens is used to estimate the ToF of the ultrasonic signal [114]. An earliest peak search method was implemented in [164] to remove multi-path interference, where the earliest peak of the correlation which is above the noise floor and which might not necessarily be the highest peak was considered as the correlation peak of the direct path. However, when the multi-path component lies closer to the line of sight (LOS) component so that the distance between the LOS

and the Non-line of sight (NLOS) component is less than the range resolution of the signal, we cannot identify separate peaks in the correlation signal at the receiver. In this case, the peaks corresponding to LOS and the NLOS cannot be differentiated. A super-resolution technique based on MUSIC algorithm was implemented in [173–175]. The techniques based on MUSIC or matrix pencil [176] are computationally intensive as they involve the computation of each singular eigenvector and corresponding eigenvalue [175]. A phase-correlation method was implemented to get a sharp peak at the correlation output [116]. However, this method cannot be used in a noisy environment. Interpolation methods were used on the obtained correlation using narrowband chirp signals in [177, 178] which cannot always provide accurate results and takes more time for analysis. In this chapter, a method to reduce the ranging errors caused by close multi-path interference is discussed.

We propose a novel multi-path compensation method for the ultrasonic indoor localization and gait analysis system. The contribution of this chapter is the adaptation of the concept of half-peak detection from radiofrequency systems [179] to indoor ultrasonic localization system and gait analysis. We further extend this idea to other fractional peak detection methods to evaluate the performance. The idea of half-peak detection to reduce multi-path errors was never used in ultrasonic systems. We propose an earliest $\frac{1}{m}$ peak detection algorithm in ultrasonic localization system and use this for gait analysis. Initially, we do the simulation experiments followed by the ranging experiment and the gait analysis with five healthy subjects. We compare the performance of the system with an optical motion tracking system.

5.2 Proposed Method

In the proposed method, linear chirp signals are used for ranging. Chirp pulse compression is the process of transforming a long duration frequency-modulated pulse into a narrow pulse with much higher amplitude. The pulse compression process can be considered as an application of the matched filter system. Let $g(t)$ be the impulse response of the transmitter coding filter. Then, the response of the matched filter at the receiver should be $g^*(-t)$, where $g^*()$ represents the complex conjugate of $g()$ and the output of the matched filter receiver can be given as shown

in Equation (5.1).

$$y(t) = \int_{-\infty}^{\infty} g(\tau)g^*(t - \tau)d\tau \quad (5.1)$$

In chirp compression process, consider $g(t)$ as a linear chirp signal multiplied by a rectangular window function given by

$$g(t) = \text{rect}\left(\frac{t}{T}\right)e^{2\pi j(f_s t + kt^2/2)} \quad (5.2)$$

From Equation (5.1) and (5.2), the output of chirp compression process, $y(t)$ can be derived as

$$y(t) = \sqrt{TB} \times \frac{\sin(\pi Bt)}{\pi Bt} \times \sqrt{j}e^{j2\pi(f_s t - kt^2/2)} \quad (5.3)$$

where, T is the chirp duration, B is the chirp bandwidth and f_s is the starting frequency. If we transmit a linear chirp signal with signal duration T seconds, the output, $y(t)$ will be a waveform with sinc characteristics with signal duration $2T$ seconds. In traditional ultrasonic ranging methods [114], the time at which the peak of $y(t)$ happens is taken as an estimate of the ToF. The low cost and low power piezoelectric transducers come with a narrow bandwidth of around 2-10 kHz. We use the frequency range from 39 to 41 kHz with MA40S4S/R transducers from MURATA Electronics. We select linear chirp signals as they are robust in terms of Doppler sensitivity and frequency selective fading [180]. Non-linear chirp signals give better results when the time-bandwidth product is higher, which is 14 in our experiments. Also, non-linear chirps give higher side lobes in the presence of Doppler effect which affects accurate range measurements [181]. Hence, linear chirp signals are used in our experiments. A block diagram to illustrate the proposed ranging method with multi-path compensation and Doppler correction is shown in Figure 5.1.

5.2.1 Compensation of Errors due to Close Multi-path Components

In the chirp compression process, the range resolution of an ultrasonic ranging sensor is the minimum separation of two targets ranging using the same signal that can be identified as separate targets from the received signals. The range resolution of the ultrasonic ranging in the ideal case with a chirp signal multiplied

FIGURE 5.1: Block diagram illustrating the proposed ranging method.

by rectangular window function can be given by $v/\delta f$, where v is the speed of sound and δf is the bandwidth of chirp. In this study, we consider linear chirp signal from 39–41 kHz, thus $\delta f = 2$ kHz and the range resolution was found to be 172 mm when the speed of sound was 345.3 m/s. If the extra path length of the multi-path component lies within 172 mm, which is quite likely to happen in a multi-path environment, there might not be two separate peaks, and the resultant peak can be shifted in the time axis. The earliest peak detection algorithm explained in [164] fails here, leading to errors in the measured value. Let T_p be the position of the peak value of correlation signal mentioned in Equation (5.1) and P_0 be the peak value. In a close multi-path environment, the position of the peak will be shifted to $T_p + X$, where X represents the error. Now, instead of taking P_0 to calculate the ToF, we propose to take $\frac{P_0}{m}$ crossing point to the left of earliest peak instead of the actual peak of the absolute value of the correlation waveform to calculate the ToF. The earliest $\frac{1}{m}^{th}$ peak will be less affected by the close multi-path components as the multi-path components travel a higher distance than the LOS path and hence appears time-shifted in the cross-correlation of the received signal with the originally transmitted signal. Since the correlation output at the receiver is sync signal with the chances of corruption by the multi-path components higher at the descending part of the main peak as shown in Figure 5.2, the chances of shift in time domain at the earliest $\frac{1}{m}$ peak point (ascending part of the main peak) will be less. In this work, the value of m is chosen out of 2, 3, and 4 by conducting simulations with 10000 iterations with different multi-path components each time. However, $\frac{P_0}{m}$ should be kept at a safe margin above the channel noise floor. We selected the value of m as 2, 3 and 4 for simulation experiments keeping $m=1$ for conventional method and the best value was chosen for implementation in the

proposed gait analysis system. The pictorial representation of the envelope of correlation peak with component from NLOS1 and the proposed fractional peak detection method is shown in Figure 5.2. Since we are removing any constant offset which is present in the range measurement, we are concerned only about the relative distance between two range measurements of the same transmitter. Even though the existence of a close multi-path shifts the time at which the correlation peak happens, the earliest $\frac{1}{m}$ × peak point will be less affected compared to the actual peak. The chirp signals can be multiplied with various kinds of window functions to increase the sensitivity and to reduce the amplitude of side lobes in the signal [182]. We test the performance of three different window functions (rectangular, hamming, and hann) along with the proposed method. Let $S(t)$ be the transmitted chirp signal multiplied by the window function, $W(t)$ given by Equation (5.4).

$$S(t) = W(t) \times \exp\left\{j2\pi\left(f_s t + \frac{1}{2}(f_e - f_s)t^2\right) + \phi\right\} \quad (5.4)$$

where, f_s , f_e and ϕ represents the starting frequency, the ending frequency and the initial phase respectively. The received signal without any multi-path components can be represented as

$$\hat{S}(t) = A(h(t) * S(t)) \quad (5.5)$$

where, A , $h(t)$ and $*$ represents the amplitude after path loss, channel impulse response and the convolution operator respectively. Considering M multi-path components, the correlation of received signal can be given by Equation (5.6).

$$C(t) = \left(\hat{S}(t) + n(t)\right) \star S(t) + \left(\sum_{m=1}^M A_m \hat{S}(t - \tau_m) + n(t)\right) \star S(t) \quad (5.6)$$

where, $\star$, $n(t)$, A_m and τ_m represents the correlation operator, channel noise, the amplitude and the extra path travelled by the multi-path components respectively. In Equation (5.6), the actual ToA information from LOS path is embedded in the first term. The second term in Equation (5.6) is the multi-path noise. Our hypothesis is that the earliest point at which the value of $C(t)$ crosses $\frac{1}{m}$ (where, $m > 1$) of the peak of $C(t)$ will be less affected by the multi-path components (the second term in Equation (5.6)) in time axis compared to the peak of $C(t)$. This is because the multi-path components appear at a later time compared to the LOS path.

5.2.2 Doppler Compensation in the Received Signal

Moving sensor nodes emitting ultrasonic waves create Doppler effect and this alters the actual range measurements. A Doppler compensation method with linear up- and down-chirp signals (Range-Doppler coupling neutralization method) was found to perform better compared to other methods in Chapter 4. Even though linear chirp signals show higher Doppler-tolerance, range-Doppler coupling leads to an error which is proportional to the moving velocity. For down-chirp signals, the error due to Doppler effect will be the same in magnitude with different polarity to that of up-chirp signals. In our experiments, in each ranging cycle of 40 ms, ranging with up-chirp was conducted in the initial 20 ms and with down-chirp in the next 20 ms duration. The chirp duration was selected as 7ms as we allocated 20 ms for up-chirp and 20 ms for down-chirp and out of 20 ms, 13 ms time was provided between two signals so that the echo will die out completely. Let R_1 , R_2 and R_0 be the range estimated from the up-chirp, down-chirp and the actual range respectively. Then,

$$\begin{aligned} R_1 &= R_0 + \dot{R} \times f_0 T / B \\ R_2 &= R_0 - \dot{R} \times f_0 T / B \\ R_0 &= (R_1 + R_2) / 2 \end{aligned} \tag{5.7}$$

where $\dot{R}$ represents the Doppler velocity of the moving target

5.3 Simulation Results

A customized ranging environment with one transmitter and one receiver was simulated in Matlab to test the performance of the multi-path compensation technique. The amplitude of signal after attenuation in the air was modeled as $A = A_0 e^{-\gamma \times \delta d}$, where A_0 and δd are the originally transmitted amplitude and the distance traveled through the medium respectively. The value of attenuation constant, γ was selected as 0.17 Np/m. The ranging was done with a chirp signal with linearly increasing frequency from 39 to 41 kHz in 7 ms. To test the performance of other

non-linear chirp signals, a simulation was conducted to find the performance of linear, logarithmic and quadratic chirp signals to estimate the Doppler-velocity using the method explained in Section 5.2.2 with 1000 iterations. The results show that the performance of the linear chirp was better than the logarithmic and quadratic chirp signals. Linear chirp signals are more sensitive to Doppler shift in the case of medical ultrasound imaging compared to other non-linear and coded chirp signals [183]. Since the time-bandwidth product in our case is a small value (14), linear chirp signals are less affected by the broadening of the main pulse and increased sidelobe levels. The reason for the superior performance of the linear chirp signal is the linear dependence of the error in range with the Doppler velocity (range-Doppler coupling). Linear frequency modulation is easy to implement, and it is also less affected by Doppler effect compared to non-linear frequency modulated signals [184]. A close multi-path component (NLOS1) with a reflection coefficient of 0.9 was provided at random positions so that the difference between the LOS and the NLOS was less than the range resolution which is 172 mm in this case. The relative distance between two LOS values, which were set to 1000 mm and 2000 mm respectively was calculated to find the improvement in ranging accuracy using our proposed method and the classical peak detection method [114]. A Monte Carlo simulation with 10000 iterations was done to estimate the distance at each position with random multi-path reflections. We selected the time index at which the cross-correlation of the received signal with the original signal crosses $\frac{1}{m}$ of its earliest peak value for the first time as an estimate for the LOS path. The plots of the correlation waveform from the LOS, NLOS, and the combined signal with $m = 2, 3$ and 4 points marked are shown in Figure 5.2.

The results obtained when the transmitted signals are multiplied by three different kinds of window functions are as shown in Table 5.1, where, I_{av} , I_{max} , D_{av} and D_{max} represent the average improvement, maximum improvement, average degradation, and maximum degradation in absolute error compared to peak detection respectively. Out of 10000 iterations, $N(I)$ and $N(D)$ are the numbers of cases with improvement and degradation respectively, and the ratio of average improvement to average degradation was calculated as $R = I_{av}/D_{av}$. To find the changes in the ratio, R as the value of m changes, we repeated the same simulation experiment with 10,000 iterations and a rectangular window function with 10 dB channel SNR for each value of m increasing from 1 to 4 in steps of 0.1 and the plot of R against m was shown in Figure 5.3. It can be observed that R slightly

FIGURE 5.2: The envelope of correlation for LOS, one NLOS component (NLOS1) and the combined waveform.

FIGURE 5.3: The plot showing variation of $\mathbf{R}$ as the value of $\mathbf{m}$ increases for a rectangular window function.

decreases after $m = 1.9$ as the value of m increases. We can also observe a sudden increase in $\mathbf{R}$ as m changes from 1 to 1.1. We found that the 'hann' and 'hamming' windows showed better results in terms of the ratio, $\mathbf{R}$ for $m = 3$ and 4, which can be explained by lower side lobes obtained for the correlation output $y(t)$. With the attenuated side lobes, the time shift by the multi-path component in the $\frac{1}{m}$ peak also decreases, thus resulting in better $\mathbf{R}$ values. However, it should be noted that as the value of m increases the estimate is getting closer to the noise floor and chances of errors and $\mathbf{D}_{max}$ also increase. Hence, the optimum value of m depends on the peak value of cross-correlation and noise power. By windowing the originally transmitted pulse, we are obtaining lower sidelobe levels in the compressed pulse. It can also be observed that the maximum degradation of accuracy

TABLE 5.1: Comparison of improvement and degradation of tracking performance of the system with earliest $1/m$ peak detection.

Window	m	I_{av} (mm)	D_{av} (mm)	I_{max} (mm)	D_{max} (mm)	N(I)	N(D)	R
Rectangular	2	14.8	8.4	55.8	35.9	6897	3046	1.76
	3	16.8	10.1	63.4	44.1	6826	3117	1.66
	4	18.2	12.4	68.3	55.2	6614	3336	1.47
Hann	2	21.6	10.9	104.8	116.5	7129	2826	1.98
	3	24.6	12.2	119.3	253.7	7135	2825	2.01
	4	26.5	14.2	118.6	446	7125	2842	1.87
Hamming	2	22.2	10	97.9	69.6	7365	2603	2.22
	3	25.9	11.3	120	129.6	7300	2660	2.29
	4	27.7	12.4	117.9	253.8	7310	2654	2.24

TABLE 5.2: Comparison of improvement and degradation of tracking performance of the system with different SNR levels.

SNR	m	I_{av} (mm)	D_{av} (mm)	I_{max} (mm)	D_{max} (mm)	N(I)	N(D)	R
10 dB	2	14.8	8.4	55.8	35.9	6897	3046	1.76
5 dB	2	15	8.9	57.9	53.8	6900	3038	1.69
0 dB	2	16.1	11.5	206.1	2040.7	6670	3272	1.4

is higher for 'hann' and 'hamming' windows. The maximum degradation increases as we multiply the signal with a window function. This is due to the decrease in the signal power of the compressed pulse as we increase the value of m and the detection point approaches the noise floor faster than the case without windowing. Hence, the chances of very high errors increase. The simulations experiments were repeated at different SNR levels and the results are listed in Table 5.2. The maximum degradation and R were found to be acceptable for 5 dB SNR; however, the maximum degradation increased about four times when the SNR level was decreased to 0 dB.

We conducted a simulation with 10,000 ranging trials with random multipath components using the proposed method and observed that the ranging performance was improved in some cases and degraded in some cases compared to classical peak detection method. In Figure 5.4, average improvement and average degradation in

the absolute error while ranging with linear chirp signals multiplied with rectangular window and a channel with 10 dB SNR is shown. The value of m is changed from 1 to 4 in steps of 0.1. From Figure 5.4, it can be observed that both the value of average improvement and average degradation increases as the value of m increases. It should be noted from Table 5.1 that the improvement is always higher than degradation for a signal multiplied by a rectangular window. For further analysis, we consider only integer values of m to make the computations easier. Keeping the average degradation at 10 mm and maximum degradation less than 40 mm leaves us with the only option $m=2$. Thus, we selected $m = 2$ and a rectangular window function at the transmitter side for our tests using ultrasonic sensors for further analysis.

The Empirical Cumulative Distribution Function (ECDF) for the errors in range estimation from the proposed method and the conventional peak detection method was calculated for rectangular window function, and $m = 2$ and plotted in Figure 5.5. The plot shows that the proposed method outperforms the conventional peak detection method in a high multi-path environment.

FIGURE 5.4: The plot showing average improvement and degradation in absolute error with the proposed method as the value of m changes.

FIGURE 5.5: The Empirical CDF calculated for ranging error in meters (X) using half-peak detection method and conventional peak detection method.

5.4 Materials and Methods

Initially, we conduct ranging experiments with one static transmitter and receiver in an indoor environment followed by the gait analysis experiment with four fixed receivers and one mobile node. Murata MA40S4S and MA40S4R ultrasonic transducers are used for ranging with chirp signals. These sensors have a narrow bandwidth with 40 kHz center frequency. The transmitter node was designed on an STM32F4-discovery development board which has a form factor, 66 mm $\times$ 97 mm. However, in the future, this system can be printed on a flexible wearable band to make it easier and unobtrusive to use. The mobile node was powered by an 11.1v Li-Po battery and a 5v voltage regulator. So the driving voltage of the ultrasonic transmitter was 11.1v. No wired connections were limiting the movement of the subject as we used wireless clock synchronization between the mobile node and the anchor nodes using 2.4 GHz wireless modules. The attachment of the mobile node to the lower limb is as shown in the Figure 5.6. The chirp signals were stored in the memory of the development board and are sent periodically to the transmitters through digital to analog converters and a driver IC (SN754410) using direct memory access. At the receiver side, we used a bandpass filter, an amplifier, and a data acquisition board. ADCs with the same resolution (which was 125 kilo-samples/s in our experiments) can replace the data acquisition board in the future.

The power consumption of the mobile node is important in wireless sensors nodes as the mobile nodes are battery-powered. Here the main part of power consumption comes from the memory access and the driving of ultrasonic transducers. We used STM32F4-discovery board to develop the sensor node and SN754410 as the driver for MA40S4S transmitter. Murata MA40S4S transmitters have 120 dB Sound Pressure Level (SPL) at 40 kHz (where, 0 dB = 0.02 mPa). An 11.1v battery and IC-SN754410 drove these transmitters. At ambient temperature, the absolute maximum continuous power dissipation in the driver IC is 2.075 W from the datasheet. The power dissipation in the development board assuming dynamic run mode at 180MHz clock frequency is 0.22 W. The total power consumption is 2.295 W. Hence, the total energy required for one ranging cycle is 0.0918 J. With the rechargeable Lithium-Polymer batteries with 11.1v and 1300mAh to power the mobile nodes, approximate battery life can be estimated as 6.29 hours. Here we neglected the power consumption in the voltage regulators. In the future, custom-designed circuits can greatly reduce power consumption. Optical motion capture system with six high-speed infrared cameras was used as the reference for the experiments.

5.4.1 Ultrasonic Ranging Experiment

For the ranging experiment, we used both up-chirp and down-chirp, and the average value was calculated using the proposed half-peak method ($m=2$) and classical peak detection method. The transmitted signals were multiplied by rectangular window functions. Measurements were taken with ten different positions of the transducers each for a low multi-path environment and a high multi-path environment. In the low multi-path environment, the transducers were placed about 750 mm above the ground with a line of sight and without any obstacles in the vicinity. In the high multi-path environment, three obstacles with flat surface were introduced near the transmission path to reflect the ultrasonic waves.

5.4.2 Gait Analysis System

A wireless gait analysis system was designed to test the proposed method. An ultrasonic mobile node was attached to the left lower limb of the subject, as shown

in Figure 5.6. For spherical localization, four static anchor nodes at the corners of a 250×200 mm rectangle were mounted on a vertical board and kept parallel to the sagittal plane at about 1000 mm from the treadmill as shown in Figure 5.7. The reflective markers of the motion capture system were attached beside the ultrasonic transmitters. We kept 15 mm distance between the ultrasonic markers and the optical markers to avoid the ultrasonic signals being blocked by optical markers and this correction was done during post-processing. The error between the optical marker and the ultrasonic sensors can be ± 1 mm as we used a measurement tape of least count 1 mm to fix the markers. The optical markers were placed at a fixed distance from the ultrasonic sensors so that the markers do not interfere with the ultrasonic transmission. The distance between the ultrasonic sensor and the optical marker is measured using a measurement tape with least count 1mm and fixed before the calibration. Five healthy subjects (four males and one female) with age between 24 to 31 were recruited for the gait analysis study. Each subject was asked to do a treadmill walk for one minute for each walking speed of 1, 2, and 3 kph with both ultrasonic mobile node and the camera marker attached to one lower limb. All participants gave their informed consents before they participated in the study.

FIGURE 5.6: The mobile node and camera marker attached to left lower limb [4].

FIGURE 5.7: The anchor nodes attached on a vertical board along with the anchor nodes [4].

Doppler shift affects the performance of the system. We took the average of the range estimated from linearly increasing and decreasing chirp signals to offset these errors as explained in Section 5.2.2 [7]. Each ranging cycle consists of two ranging each with 20 ms duration, first one with an up-chirp from 39 to 41 kHz in 7 ms and a second one with a down-chirp from 41 to 39 kHz in 7 ms. A separation of 13 ms was thus provided between any transmitted signals. We estimated the measurements each 20 ms by taking the mean value of up and down-chirp ranging cycles from adjacent ranging cycles. Therefore the total update rate of the system was about 50 Hz. Both half-peak detection method ($m = 2$) and classical peak detection method ($m = 1$) were implemented for all the range measured from all the four ultrasonic anchor nodes in the gait analysis system. The state-space equation for calculating the x, y, and z coordinates from the measured distances is as described in Chapter 3. In the measurement model, the standard deviation of ultrasonic measurements, $\mathbf{e}$ was set to 5 mm in our system. An Unscented Kalman Filter (UKF) [149] along with an Unscented Rauch-Tung Striebel smoother [150] was implemented to obtain the three-dimensional trajectory from the measured distances and the state space equation explained in Chapter 3. All the trajectories were low pass filtered using a butter-worth filter with a cut off frequency of 10 Hz.

5.5 Results and Discussion

Static measurements were taken with one transmitter and one receiver placed at ten different positions each for a high multi-path and relatively low multi-path

environments. The first measurement was subtracted from the remaining nine measurements to obtain the differential distances. The differential distances calculated from the proposed and the classical peak detection methods were compared to the camera distance measurements to obtain the mean error. The standard deviation of distance calculated at each static position was also calculated. The results are provided in Table 5.3.

TABLE 5.3: Comparison of mean error in differential distance (ME) calculated from the proposed and the classical methods and the standard deviation in the static measurement using up-chirp (S_u) and down-chirp (S_d).

Method	High Multi-Path (mm)			Low Multi-path (mm)		
	ME	S_u	S_d	ME	S_u	S_d
Proposed	26.63	2.66	2.61	7.70	2.27	2.26
Classical	44.10	10.34	10.41	22.24	10.68	10.32

It can be observed that we were able to get consistent and considerable improvement in the precision of the system using the proposed method. In both high and low multi-path conditions, the average standard deviation for static measurements decreased considerably from 10.44 mm in classical method to 2.45 mm in the proposed method. Figure 5.8 shows the static measurement reading obtained from the classical peak detection and the proposed half-peak detection methods after removing the offset between the measurements. The proposed method provides stable measurements readings compared to the classical method. The distortion in the static measurement is due to the random errors and multi-path interference. The distortion seems cyclic as an error of one sample translates to about 3 mm error in distance which contribute to granular noise in the proposed method. In the classical method, the errors will be higher due to close multi-path components.

FIGURE 5.8: The static measurements obtained from the ultrasonic system using the classical [5] and the proposed methods.

The mean error and standard deviation of the error (STD Error) and root mean square error (RMSE) between the ultrasonic system and the camera system during gait analysis experiments are provided in Table 5.4. Any temporal delay between the foot trajectory from the ultrasonic system and the camera system was removed before analysis. The net RMSE from the proposed method was found to be 22.28 mm compared to 28.70 mm from the classical peak detection method.

TABLE 5.4: Comparison of mean values of error in estimated coordinates from the proposed and the classical methods during the gait analysis experiments.

Method	Proposed Method (mm)			Classical Method (mm)		
Coordinate	x	y	z	x	y	z
Mean Error	-0.94	-0.05	0.61	-0.97	0.24	0.19
STD Error	15.92	8.09	12.71	18.96	9.68	18.04
RMSE	16.04	8.14	12.92	19.32	9.79	18.40

The RMSE obtained for each subject along the 3D coordinates are listed in Table 5.5. The time complexities of one ranging cycle using all the methods are $O(n)$, where n is the number of samples in the correlation waveform, which means complexity of all methods grow linearly with the signal length. The threshold based earliest peak detection generally needs less computation time compared to highest

TABLE 5.5: Comparison of RMSE in estimated coordinates from the proposed and the classical methods during the gait analysis experiments.

Subject	Axis	Classical			Proposed		
		1 kph	2 kph	3 kph	1 kph	2 kph	3 kph
1	X	16.77	13.72	14.97	14.40	11.96	13.61
	Y	7.70	7.43	9.14	7.09	6.93	8.50
	Z	8.89	9.68	10.89	6.94	7.76	8.99
2	X	17.24	17.62	22.88	14.08	15.20	21.33
	Y	8.24	9.57	8.65	7.27	9.03	8.04
	Z	13.39	16.69	15.20	10.44	13.48	12.27
3	X	19.65	16.45	18.15	14.67	14.24	16.29
	Y	7.62	7.73	8.23	5.98	6.96	7.91
	Z	18.05	15.92	16.96	13.37	11.52	13.54
4	X	13.41	20.31	24.61	11.51	17.78	22.97
	Y	8.78	9.62	11.43	7.77	8.86	10.90
	Z	14.72	17.52	19.78	11.01	14.58	17.19
5	X	22.41	31.61	19.99	15.27	19.19	18.17
	Y	16.21	16.33	10.21	8.31	9.22	9.37
	Z	40.27	34.44	23.62	17.11	16.14	19.45

peak detection as we can stop searching after finding the first peak which is greater than the threshold. The earliest ($1/m$) peak detection requires one division operation of earliest peak value by m and a search in reverse direction to find the index of the half-peak. Hence, we can conclude that the computational complexity of the proposed method can be lesser than highest peak detection method if the earliest peak comes much earlier than the main peak; however, we need to do one division operation in the proposed method.

5.5.1 Comparison of Estimated Gait Parameters

To quantify the performance of the proposed system with respect to the reference system, the mean, the standard deviation and the RMSE between the parameters from both systems during treadmill walk with walking speed 3 kph are calculated and listed in Table 5.6. The proposed system gave good results for the estimation of stance time, swing time, and maximum foot clearance. A Wilcoxon rank sum test was conducted to test the hypothesis that the gait parameters estimated from

TABLE 5.6: Comparison of mean and standard deviation (STD) of gait parameters estimated from the ultrasonic system and the reference camera system at 3kph walking speed.

Subject			1	2	3	4	5
Stride Length (mm)	Camera	Mean	998.56	898.76	1027.4	1225.78	932.1
		STD	64.07	93.12	47.89	111.06	125.93
	Ultrasound	Mean	1024.81	871.21	1011.71	1239.3	917.06
		STD	63.11	94.02	53.01	118.59	128.34
	RMSE		28.87	37.7	24.62	27.82	29.45
Stance Time (ms)	Camera	Mean	802.08	648.93	720.27	835.92	645.72
		STD	35.34	59.98	77.79	44.83	35.44
	Ultrasound	Mean	798.12	642.95	714.64	833.9	631.98
		STD	36.52	63.97	84.06	40.27	38.86
	RMSE		16.4	15.79	15.19	10.61	19.33
Swing Time (ms)	Camera	Mean	521.46	402.78	459.91	483.33	431.76
		STD	13.19	21.57	25.29	26.82	19.03
	Ultrasound	Mean	525	408.76	465.76	484.48	445.04
		STD	16.77	23.49	25.74	32.02	19.88
	RMSE		15.65	15.45	16.78	12.95	17.27
Max. Foot Clearance (mm)	Camera	Mean	140.24	107.49	125.63	130.61	146.2
		STD	6.05	10.87	10.82	9.89	14.11
	Ultrasound	Mean	143.55	103.56	121.11	143.56	135.36
		STD	9.42	13.7	15.29	13.67	16.94
	RMSE		9.12	10.42	11.58	16.47	15.19

the ultrasonic and camera system came from a continuous distribution with equal medians. The tests failed to reject the null hypothesis with $p > 0.05$. The Bland-Altman plots for the step lengths and swing times obtained from both systems are shown in Figure 5.9. The limits of agreements ($\pm 2 \times SD$) obtained for step length and swing times are [25.45 -23.31] mm and [24.80 -34.80] ms respectively.

FIGURE 5.9: Bland-Altman plots comparing (a) step lengths and (b) swing time calculated from the proposed system with the motion capture system at 3 kph walking speed for a subject. The upper and lower limits are marked as mean difference $\pm 2 \times$ standard deviation(SD)

5.6 Conclusions

A new method of multi-path tolerant ultrasonic ranging and localization was proposed. The simulation experiments with earliest $\frac{1}{m}$ value detection show that $m = 3$ and 4 performed better in terms of ratio, R when the transmitted wave is multiplied by a 'hann' or a 'hamming' window. However, the maximum value of degradation increased for these window functions and m values. We implemented the half-peak detection method with $m=2$ and a rectangular window function on chirp signals and ultrasonic transducers. The proposed half-peak detection was found to perform better than the classical peak detection for the coherent receiver in an ultrasonic ranging system with static transducers as well as the localization system for gait analysis with one moving transmitter. The gait analysis system with one ultrasonic marker attached to one lower limb was found to give better results with net-RMSE 22.28 mm for the proposed method compared to 28.70 mm for the classical method. The net-RMSE was found to be 19.86, 21.81, and 25.16 mm respectively for 1, 2, and 3 kph walking speeds respectively. The system gave good results for the estimation of spatial and temporal parameters from the proposed

system. However, the method was tested for only cases with one mobile node. The performance of the method in the presence of multiple access interference needs further study.

Chapter 6

Gait Symmetry and Joint Angle Estimation Using Ultrasonic Sensor Network and Spatial Division Multiple Access

We studied the localization of one mobile node and its application in gait analysis in the previous chapters. With one mobile node, we can track only one limb during gait analysis. To study about bilateral gait and joint angles, we need more than one wireless nodes to be tracked simultaneously. In this chapter, a spatial division channel multiple access method for tracking more than one ultrasonic mobile node is proposed and investigated. The system was then used for gait analysis. The directionality and spatial orientation of narrowband ultrasonic sensors were exploited for different sensors to transmit ultrasonic signals at the same time. In the second part of this chapter, a joint angle tracking method with only two wearable mobile nodes is explained with a simulation study.

6.1 Materials and Methods

In ultrasonic localization systems, Spatial Division Multiple Access (SDMA) can be defined as the channel multiple access method by separating the transmission direction of different ultrasonic transmitters. We tested the performance of SDMA

FIGURE 6.1: Sensors used:(a) SRF02 Ultrasonic sensor, (b) 434 MHz. RF transmitter and receiver.

using narrowband ultrasonic ranging sensors in our prototype for bilateral gait analysis. Four anchors are enough to track three-dimensional coordinates of a single mobile node. Ultrasonic sensor network with two mobile nodes and eight anchor nodes were employed to estimate the three-dimensional position coordinates of two markers attached to the lower extremity. In this system, we are exploiting the spatial arrangement of the sensors to track multiple points without interference. That is, we are using a different set of receivers for each mobile node. We need four anchor nodes for tracking one mobile node [30]. Hence, we need eight anchor nodes for simultaneously tracking two mobile nodes using spatial division multiple access. The ToA of the ultrasonic waves from each mobile nodes to a set of four receivers is calculated. Both transmitters are configured to transmit at the same time. Even though we used a different ultrasonic transducer in this experiment, we are only using monotonic signals with simple threshold detection and thus, the tracking performance is not much dependent on the frequency characteristics of the sensors. The range and transmission beam pattern of the two sensors are different and this mainly affects only the capture volume of the sensor systems. The receiver set consists of eight SRF02 ultrasonic sensors by Devantech Ltd., UK (Figure 6.1) connected by Inter-Integrated Circuit (I²C) bus to an Arduino UNO controller and the eight sensors were divided into two sets of four each attached to the corners of two rectangles. Each mobile node consists of one SRF02 ultrasonic sensor attached to an Arduino UNO controller by I²C connection. We use an outside-in tracking system where the anchor nodes estimate the position of mobile nodes after receiving the pulses transmitted by the mobile nodes. It provides better accuracy, less computational overhead, and longer battery life compared to inside-out tracking when the number of mobile nodes is less than that of the number of anchor nodes. The SRF02 ultrasonic sensors provide a radiation angle of 55 degrees and a maximum range of 6 meters and hence give enough coverage for small scale localization for human motion-capture during treadmill walk. Low cost 434 MHz

Radio Frequency (RF) transceivers (Figure 6.1) were used to synchronize the time between two transmitters and receiver set by sending one byte of data before each cycle of data measurement. The accuracy of the measurement depends highly on the clock synchronization between the ultrasonic transmitters and receivers; hence the overheads in RF communication were removed to prevent jitter and delays. We have used simple Amplitude Shift Keying (ASK) using 434MHz transceivers for sending the synchronization messages, and the bit rate for RF communication was set to 8000 bits per second. Short messages without re-transmit or acknowledgment were used to reduce overheads. The maximum packet length was estimated to be 408 bits and the transmission speed was set to 8000 bps. Offsets in the measured value were added to compensate for delays in the transmission of the RF signal. The eight ultrasonic receivers were connected to a single controller and each sensor was identified by a unique address. The receivers were polled serially. The delays in sending the command to sensors were evaluated by experiments and accounted for by adding offsets to the measured value. The configuration of the system is shown

FIGURE 6.2: The experiment setup with ultrasonic transmitters attached to the body and receivers connected to the Arduino board.

in Figure 6.2. The proposed system consists of eight ultrasonic receivers connected to a coordinator (Arduino UNO) through a wired connection, and the coordinator is connected to a personal computer through a serial port. Each measurement cycle is initiated by the coordinator, which sends a byte of synchronization signal through RF modules. At the same time measurement start commands are given to each of

the eight ultrasonic receivers. As soon as the mobile nodes receive the RF signal, eight ultrasonic pulses are transmitted from both transmitters simultaneously. In this experiment, we used monotonic ultrasonic pulses for ranging. Each receiver records the time of arrival of the ultrasonic pulses, and the data is passed to the personal computer through a serial port. The distance between the transmitters and the fixed receivers is given by $d = v \times t$, where t is the measured time and v is the approximate velocity of sound in air at ambient temperature which is given by [81]: $v = 331.5 + 0.6 \times T$. Temperature, T was maintained at about 22°C during this experiment. The measurement cycle is repeated every 66 ms. Thus the update rate of the system is about 15 Hz. The localization of the mobile node was done considering the system model explained in chapter 3. The measurement noise in each range estimation, e was calculated as 8.11 mm from experiments. The measurements from both legs were synchronized as all the anchor nodes were connected to a single control board. Data analysis was done offline using Matlab (MathWorks, USA).

6.2 Experiment Methods and Data Analysis

Five healthy subjects (3 Males and 2 Females) with age (26 ± 1.67) years height (168.2 ± 4.26) cm and weight (61.08 ± 7.55) Kg were recruited for experimental validation of the setup. All the subjects gave informed consents to take part in the experiment. All the subjects involved did not have any history of severe injury or neurovascular disorders and did not involve in severe physical activities 24 hours prior to the experiment. Ultrasonic sensors and reference markers of camera system were attached to the shank of each foot with velcro tape just above the ankle joint so that the approximate angle between the two ultrasonic beams was 180° which avoids the interference of signals from each limb. The placement of the sensor node on foot is shown in Figure 6.3. Four receivers were positioned to track one transmitter on either side of the body. 3D positions coordinates of the eight anchors in millimeters were (0,0,0) , (324,0,0), (0,230,0), (324,230,0), (0,0,2000) , (324,0,2000), (0,230,2000) and (324,230,2000). Each subject carried out a treadmill walk at fixed walking speeds of 1, 2 and 3 kph each for five minutes with about a minute's break in between. Both systems were started at the same time and

FIGURE 6.3: Placement of the sensor on the foot

the time shifts between the two systems were adjusted by maximizing the cross-correlation between the signals in the post-processing. Large outliers in ultrasonic data were removed. Linear interpolation was used to match the sampling rate of the system with the camera system which is 120 Hz, and the data were passed through a low pass filter of cut-off frequency 7 Hz. We selected 7 Hz as the cut-off frequency as the frequency content of normal gait when walking at less than 3 kph was found to be very less. To extract the spatial and temporal gait parameters, we plotted the frequency response of the X-axis data and it did not increase more than 7 Hz. In the system we developed in this chapter, the ranging pulse repetition frequency was 15 Hz, and this sampling frequency can capture a maximum frequency of only 7.5 Hz. The RMSE between the signals from the motion capture system and the ultrasonic system was used to compare the accuracy of tracking. Heel-strike (HS) and Toe-off (TO) were detected, as explained in Chapter 3. The time of HS and TO were compared to that of motion capture data. A temporal tolerance of ± 10 samples or ± 0.0833 s was set. The HS and TO detected within this tolerance level were considered as a successful detection. The rate of successful detection of the HS and TO events were calculated for each leg at walking speeds of 1, 2 and 3 kph. Any constant bias in the data was removed before analysis.

6.3 Bilateral Gait Symmetry Estimation

Gait symmetry was quantified in literature by using Symmetry indices or by statistical approaches [124]. A simple bilateral gait symmetry (GS) measure of gait can be quantified as the ratio of the mean swing times of one leg to the other.

$$GS = \frac{ST_l}{ST_r} \quad (6.1)$$

Where ST_l and ST_r are the mean swing times of the left limb and right limb, respectively. Before calculating the gait symmetry ratios, we removed any constant temporal offsets between the measurements of ultrasonic and optical systems. We found the mean value of bias in estimating the swing times by the proposed system considering all the measurements and removed this bias from all the measurements before calculating the gait symmetry measure.

6.4 Results and Discussions

The spatial and temporal parameters extracted from the system were compared to the reference system and Bland-Altman plots [185] were plotted. The trajectories of lower limbs of five healthy subjects during treadmill walking were extracted from the proposed system and benchmarked using the motion capture system. The plots of data obtained from the motion capture system and the proposed system for x, y, and z coordinates are provided in Figure 6.4 and the RMSE in millimeters calculated from the collected data is given in Table 6.1. The data shows a similarity between both systems and the RMSE was found to increase as the walking speed increases. A column chart showing the mean values of net-RMSE of the trajectory of right and left lower limbs at various speeds is shown in Figure 6.5. Wilcoxon Rank sum test was conducted to test the null hypothesis that the swing time distributions for both systems were identical after removing any constant bias. The test failed to reject the null hypothesis for $p > 0.05$ for left and right legs respectively at 95% confidence level. The GS values obtained from the ultrasonic system and the motion capture system were comparable and are listed in Table 6.2. The mean and standard deviation of the difference between the GS values obtained

from two different systems were calculated from Table 6.2 and was found to be (-0.0024 ± 0.0079) . We concatenated the GS values extracted from all subjects while walking at 3 kph and a Bland-Altman plot comparing the GS values estimated for both systems is shown in Figure 6.6. In our experiments, we compare the accuracy provided by our system with the gold standard. The acceptable difference of gait symmetry greatly depends on the applications. For example, if we are using the proposed system to measure the gait symmetry in hemiplegic stroke subjects, it can be observed from previous studies that the gait symmetry ratio for healthy subjects is 1.02 ± 0.02 and for stroke subjects is 1.24 ± 0.34 when swing time ratio is considered [131]. Hence, our system should be at least sensitive enough to identify the difference which is 0.22. Considering the negligible error in the camera system, we also did a Bland-Altman (Figure 6.6) analysis and found the upper and lower limits of agreements as $[0.18 -0.15]$..

TABLE 6.1: net-RMSE between ultrasound and camera data in millimeters

Subject	Foot	1 kph	2 kph	3 kph
1	Right	25.36	28.78	31.04
	Left	26.15	28.43	31.64
2	Right	27.05	35.91	39.44
	Left	28.54	38.12	43.21
3	Right	25.70	25.75	29.27
	Left	32.96	36.91	37.82
4	Right	26.96	32.32	39.20
	Left	28.95	32.16	37.05
5	Right	28.78	32.61	33.53
	Left	26.32	29.98	34.13

Bland-Altman plots with mean and difference between the step lengths and swing times extracted from the ultrasonic system and the motion capture system are shown for both lower limbs in Figure 6.7 and Figure 6.8 respectively for one subject walking at a speed of 3 kph. The limits of agreement were set to mean difference $\pm 2 \times$ standard deviation of the difference. The plots show an agreement between both systems with limits of agreements $[75.14 -34.82]$ mm, $[76.72, 9.75]$ mm respectively for the step length of left and right limbs and $[40.16 -111.28]$ ms and $[6.02 -86.74]$ ms respectively for swing time of left and right limbs. To check

FIGURE 6.4: The comparison of graphs from the ultrasound system and the camera system at walking speed of (a) 1 kph, (b) 2 kph, and (c) 3 kph. X axis shows horizontal displacement, Y represents vertical displacement and Z represents lateral displacement. The data belong to subject-1.

FIGURE 6.5: Mean net-RMSE of right and left lower limbs.

the presence of error accumulation, we segmented x-coordinate values of continuous walking trials into five parts and calculated the RMSE for various segments. We didn't observe any significant deviation from the mean value for each segment. Hence, this system can be a promising candidate for long-term analysis of gait events. A Bland-Altman plot for the mean and difference between the step width extracted from the proposed system and the camera system for one subject walking at 3 kph is shown in Figure 6.9. The limits of agreements around perfect match were found to be $[30.44 -26.83]$ mm. One heel width was subtracted in this case as we attached the sensors on the outer edge of the heels. The main drawbacks of the system are the low data update rate and the interference between ultrasonic pulses when the number of mobile nodes to be localized increases as we are employing SDMA. SDMA requires one set of four receivers to track one wearable mobile node. We need more mobile nodes spatially arranged and requires synchronization and proper alignment between each receiver sets which makes the system complex and costly as the number of mobile nodes increases. Also, if the mobile nodes to be tracked are close to each other so that they cannot be separated spatially, the proposed SDMA method fails.

FIGURE 6.6: Bland-Altman plot for comparing gait symmetry values estimated from the proposed system and the reference system for all subjects at walking speed of 3 kph.

FIGURE 6.7: Bland-Altman plots for comparing step lengths calculated from the proposed system and the motion capture system for:(a) Left leg (b) Right leg.

TABLE 6.2: GS values from Camera and Ultrasonic system at various walking speeds

Subject	System	1 kph	2 kph	3 kph
1	Camera	1.0027	0.9829	0.9900
	Ultrasonic	0.9980	0.9925	0.9886
2	Camera	0.9936	0.9969	0.9895
	Ultrasonic	0.9920	1.0025	1.0062
3	Camera	1.0188	0.9946	1.0032
	Ultrasonic	1.0169	1.0004	1.0131
4	Camera	1.0008	1.0205	1.0441
	Ultrasonic	1.0017	1.0094	1.0537
5	Camera	0.9926	0.9696	1.0145
	Ultrasonic	1.0024	0.9601	1.0132

FIGURE 6.8: Bland-Altman plots for comparing swing times calculated from the proposed system and the motion capture system for:(a) Left leg (b) Right leg.

6.4.1 Gait Events Detection from the proposed system

The time between successive sampling points in the reference system is 0.00833 s and we checked whether the error in detecting the time at which heel-strike and toe-off happens lies within ± 10 sample points which corresponds to 0.0833 s. The

FIGURE 6.9: Bland-Altman plot for comparing step width calculated from different systems.

TABLE 6.3: Percentage of correct HS and TO detection from the proposed system compared to the motion capture system.

Subject	Foot	1 kph		2 kph		3 kph	
		HS	TO	HS	TO	HS	TO
1	Right	96.00	100	98.04	100	98.71	100
	Left	100	100	100	100	100	100
2	Right	86.90	98.62	89.51	100	99.01	100
	Left	95.86	98.62	100	99.30	99.51	100
3	Right	93.14	96.00	100	100	100	100
	Left	99.43	100	98.56	99.52	99.53	100
4	Right	100	100	100	99.51	100	100
	Left	100	97.98	100	98.04	99.57	99.57
5	Right	100	100	98.48	98.98	99.53	100
	Left	100	99.46	100	98.98	100	99.53

percentage of successful detection was expressed on a scale of 0 to 100. Table 6.3 shows the detection rate of HS and TO events from the proposed system compared with the motion capture system. From the data, it is clear that the system detected heel-strikes and toe-offs with an accuracy of ± 0.0833 s 90% of the time except in two cases.

TABLE 6.4: Comparison of mean and standard deviation (STD) of gait parameters estimated from the ultrasonic system and the reference optical motion capture system for the right foot at a walking speed of 3 kph.

	Subject		1	2	3	4	5
Stride Length (mm)	Camera	Mean	902.95	965.27	871.61	979.06	911.59
		STD	47.55	63.33	51.45	75.57	45.72
	Ultrasound	Mean	894.69	915.26	835.49	955.73	891.62
		STD	58.43	67.26	81.48	80.60	78.28
	RMSE		20.05	29.33	36.85	22.80	29.95
Stance Time (ms)	Camera	Mean	726.73	813.12	679.18	785.14	772.77
		STD	29.48	27.09	33.16	48.38	31.71
	Ultrasound	Mean	723.91	809.42	667.60	772.26	745.08
		STD	46.36	37.52	43.67	58.17	58.23
	RMSE		38.54	28.49	30.97	33.62	55.56
Swing Time (ms)	Camera	Mean	453.84	493.92	438.73	476.31	468.62
		STD	15.43	20.09	20.19	29.90	22.97
	Ultrasound	Mean	455.95	497.86	450.21	489.58	496.66
		STD	40.07	27.83	31.97	39.36	43.48
	RMSE		38.34	27.02	30.13	36.74	52.28

6.4.2 Estimation of Spatial and Temporal Gait Parameters

Gait parameters such as Stride length, Swing time, Stance time were estimated for both lower limbs from the proposed ultrasonic gait analysis system as explained in Chapter 3. The mean and standard deviation of the estimated gait parameters for each subject at a walking speed of 3 kph and the RMSE between the gait parameters estimated from the ultrasonic and optical systems are listed in Tables 6.4 and 6.5 respectively for right and left lower limbs.

TABLE 6.5: Comparison of mean and standard deviation (STD) of gait parameters estimated from the ultrasonic system and the reference optical motion capture system for the left foot at a walking speed of 3 kph.

		Subject	1	2	3	4	5
Stride Length (mm)	Camera	Mean	911.20	965.70	885.34	999.68	959.72
		STD	64.00	41.18	55.83	59.24	46.28
	Ultrasound	Mean	866.18	939.53	869.60	997.35	887.30
		STD	69.53	64.30	58.61	71.75	54.98
	RMSE		27.03	25.55	18.90	19.73	40.25
Stance Time (ms)	Camera	Mean	732.95	814.69	694.69	793.83	777.95
		STD	24.81	24.15	32.60	50.60	35.03
	Ultrasound	Mean	716.99	808.29	657.16	763.14	744.47
		STD	31.28	42.26	37.56	55.80	44.32
	RMSE		28.64	38.51	43.60	41.66	43.08
Swing Time (ms)	Camera	Mean	447.24	492.39	423.41	467.98	464.40
		STD	12.35	12.75	20.49	24.05	18.24
	Ultrasound	Mean	462.93	499.39	461.36	498.41	497.89
		STD	28.39	39.17	31.12	35.81	31.55
	RMSE		29.93	37.66	44.02	42.01	42.91

6.4.3 Comparison of Velocity Estimated from Ultrasonic System with the Motion Capture Data

As mentioned in Chapter 3, the six states of the model included the velocity of the mobile node in three dimensions. The velocity of each foot can be estimated from the state space equation of the model. Here we compare the velocity of one foot estimated from the ultrasonic system to that of the optical motion capture system. The derivative of the filtered time series data from the motion capture system was used for comparison. The mean values of correlation coefficients between the systems in x and y directions were found to be 0.970 and 0.692, respectively. Figure 6.10 shows the plot comparing velocity from both systems at 3 kph walking speed.

FIGURE 6.10: Comparison of velocity from Camera and Ultrasound systems at a walking speed of 3 kph.

6.5 Joint Angle Calculation using only Two Wearable Nodes

In this section, initially, the biomechanics of human limbs and inverse kinematics to study the knee joint angle are studied. Finally, we explain a method for tracking the knee and hip joint angles during gait with only two wearable nodes using a simulation study. The knee joint plays a vital role in the locomotion of human beings. The knee joint is more prone to injuries. Here, we are mainly focusing on the tracking of knee flexion and extension angles during gait. Many types of Electrogoniometers can be used to measure the joint angles, and flexible goniometers are particularly convenient. However, they are not sufficiently robust for daily clinical usage [14]. American Medical Association recommends the mean error limit in calculating the joint angles to be less than 5° to consider the measurements reliable for evaluation of movement impairments in clinical context [62]. Many systems for joint angle estimation using IMUs and magnetometers were proposed in earlier works. All those systems were having some drawbacks like integration drift or the problems in accurate alignment of axes or issues tracking high accelerations as explained in Section 2.5.

6.5.1 Biomechanical Model of Human Limbs

In this study we consider two mobile nodes attached to the lower extremity, one at the hip (Greater Trochanter) and other at the ankle to track lower limb knee joint flexion and extension angles. The human limb model was based on a sequence of links connected by joints. The transformation based on D-H parameters [186] was used to get the coordinates of adjacent joints. The transformation can be defined by four parameters as described below:

1. θ_i : Angle between $\mathbf{x}_{i-1}$ and $\mathbf{x}_i$ along $\mathbf{z}_{i-1}$ axis.
2. d_i : distance between $\mathbf{x}_{i-1}$ and $\mathbf{x}_i$ along $\mathbf{z}_{i-1}$ axis.
3. a_i : distance between $\mathbf{z}_{i-1}$ and $\mathbf{z}_i$ along $\mathbf{x}_i$ axis.
4. α_i : Twist angle between $\mathbf{z}_{i-1}$ and $\mathbf{z}_i$ along $\mathbf{x}_i$ axis.

The transformation between two adjacent links i-1 and i is given by:

$$\mathbf{T}_{i-1}^i = \begin{bmatrix} \cos(\theta_i) & -\cos(\alpha_i)\sin(\theta_i) & \sin(\alpha_i)\sin(\theta_i) & a_i\cos(\theta_i) \\ \sin(\theta_i) & \cos(\alpha_i)\cos(\theta_i) & -\sin(\alpha_i)\cos(\theta_i) & a_i\sin(\theta_i) \\ 0 & \sin(\alpha_i) & \cos(\alpha_i) & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (6.2)$$

The link L1 corresponds to the thigh and L2 corresponds to the shank. Here, we have 3D coordinates of the knee and the hip while both of them are moving during gait. d_1, d_2, α_1 and α_2 were set to zero as we are only considering the movements in the sagittal plane. The five degrees of freedom model for knee angle calculation is shown in Figure 6.11. The coordinate system was transformed to one which is attached to the hip marker so that the origin is always at the hip marker and the axes are parallel to the original coordinate system. The transformation matrix to

FIGURE 6.11: Five degrees of freedom model for knee flexion and extension angle estimation

find the position of ankle with respect to hip is given by

$$T_0^2 = T_0^1 T_1^2 = \begin{bmatrix} \cos(\theta_1 + \theta_2) & -\sin(\theta_1 + \theta_2) & 0 & a_2 \cos(\theta_1 + \theta_2) + a_1 \cos(\theta_1) \\ \sin(\theta_1 + \theta_2) & \cos(\theta_1 + \theta_2) & 0 & a_2 \sin(\theta_1 + \theta_2) + a_1 \sin(\theta_1) \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (6.3)$$

6.5.2 Solving Inverse Kinematics Problem Using Damped Least Squares for Knee Flexion and Extension Angle Estimation During Gait

The position of ankle is given by

$$\begin{aligned} p &= f(\theta_1, \theta_2) \\ \dot{p} &= J(\theta_1, \theta_2) \begin{bmatrix} \dot{\theta}_1 \\ \dot{\theta}_2 \end{bmatrix} \end{aligned} \quad (6.4)$$

where $\dot{\mathbf{p}}$ represents the Cartesian velocity and $\dot{\boldsymbol{\theta}}_1$ and $\dot{\boldsymbol{\theta}}_2$ represent the joint angular velocities. The Jacobian matrix, $\mathbf{J}$ is given by

$$\mathbf{J} = \begin{bmatrix} \frac{\partial f}{\partial \theta_1} & \frac{\partial f}{\partial \theta_2} \end{bmatrix} \quad (6.5)$$

A general solution for joint angular velocities from Equation (6.4) using generalized inverse of Jacobian is given by [187, 188]

$$\begin{bmatrix} \dot{\theta}_1 \\ \dot{\theta}_2 \end{bmatrix} = \mathbf{J}^*(\mathbf{p} - \hat{\mathbf{p}}) + (\mathbf{I} - \mathbf{J}^*\mathbf{J})\boldsymbol{\phi} \quad (6.6)$$

where $\mathbf{J}^*$ is the generalized inverse of the Jacobian matrix. $\hat{\mathbf{p}}$ is the estimated position of ankle calculated from the forward kinematic model of the system and $\mathbf{p}$ is the measured position in the current step. $(\mathbf{I} - \mathbf{J}^*\mathbf{J})$ is the matrix which projects the vector $\boldsymbol{\phi}$ in the null space of $\mathbf{J}$ [187].

$$\boldsymbol{\phi} = \mathbf{k} \left(\frac{\partial \mathbf{w}(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right)^T \quad (6.7)$$

where $\mathbf{k} > \mathbf{0}$ and $\mathbf{w}(\boldsymbol{\theta})$ is a scalar objective function defined by joint variables. The solution moves along the direction parallel to the gradient of $\mathbf{w}(\boldsymbol{\theta})$ and the system tries to maximize the distance from mechanical joint limits.

$$\mathbf{w}(\boldsymbol{\theta}) = \frac{-1}{2n} \sum_{i=1}^n \left(\frac{\theta_i - \bar{\theta}_i}{\theta_{imax} - \theta_{imin}} \right)^2 \quad (6.8)$$

where $\bar{\theta}_i$ is the middle value of the joint angle range and θ_{imin} and θ_{imax} are the minimum and maximum limit of the i^{th} joint angle. Redundancy is exploited to keep the angle close to the middle value [189].

6.5.2.1 Damped Least Squares

The system is close to singular point when the knee angle approaches 180° and the measurement errors incurred may cause the end effector to move to some unreachable targets and this may cause oscillations in the system [190]. This can be avoided by using damped least squares while inverting differential kinematics in

the neighborhood of singularity.

$$\mathbf{J}^* = \mathbf{J}^T(\mathbf{J}\mathbf{J}^T + \lambda^2 \mathbf{I})^{-1} \quad (6.9)$$

where λ is the damping constant and is given by

$$\lambda^2 = \begin{cases} 0, & \text{when } \sigma_{min} > \epsilon \\ (1 - (\frac{\sigma_{min}}{\epsilon})^2)\lambda_{max}^2, & \text{otherwise} \end{cases} \quad (6.10)$$

where λ_{max} is the maximum value of the damping constant and was set to shape the graph at the neighborhood of singularity. σ_{min} is the estimate of the smallest singular value of the Jacobian matrix and ϵ is the size of the singular region [191]. If the joint angles at an instant i are known, the joint angles at the instant $i + 1$ are given by

$$\begin{bmatrix} \theta_1(i+1) \\ \theta_2(i+1) \end{bmatrix} = \begin{bmatrix} \theta_1(i) \\ \theta_2(i) \end{bmatrix} + \begin{bmatrix} \dot{\theta}_1(i) \\ \dot{\theta}_2(i) \end{bmatrix} \delta t \quad (6.11)$$

where δt is the sampling time. Once the initial estimate of joint angle is calculated from the previous angle value and joint velocity($\dot{\theta}(i)$) estimated using Equation (6.6), the solution can be refined iteratively until the difference between the measured position of the ankle and the position estimated from the forward kinematic equation using the estimated joint angles lies within a threshold limit.

6.5.3 Simulation Experiments for Human Knee Joint Flexion and Extension Angle Calculation during Gait

In this study, we consider motion capture data from Walking Biomechanics Data Set (WBDS) [192] for ten subjects (five younger and five elder subjects) walking on level ground. To estimate the knee joint angle during gait, we consider two markers, one at the greater trochanter and one at the ankle joint for each lower limb. The distance from hip marker to the knee (L1) and knee to the ankle marker (L2) were estimated from the marker data. We add white Gaussian noise with three different power levels of 0, 15 and 30 dbW to the 3D marker trajectory of the two selected markers, and study the error tolerance of the proposed method for joint angle calculation. The joint angles calculated using only two markers with added noise and the proposed method was compared to the actual joint angles estimated

TABLE 6.6: Mean Absolute Error between the joint angles estimated from the proposed method at various noise levels and the actual angles

Noise Power	Low (0 dbW)	Medium (15 dbW)	High (30 dbW)
Hip Angle (degrees)	2.1	2.8	9.57
Knee Angle (degrees)	4.51	5.22	14.03

TABLE 6.7: Correlation coefficient between the joint angles estimated from the proposed method at various noise levels and the actual angles.

Noise Power	Low (0 dbW)	Medium (15 dbW)	High (30 dbW)
Hip Angle	0.988	0.972	0.756
Knee Angle	0.986	0.965	0.689

by using three markers (including knee marker) and the mean absolute error and correlation coefficients between them were estimated. Figure 6.12 shows the plots comparing the hip and knee flexion-extension angles obtained from the proposed method using damped least squares inverse kinematic and the actual angles for one subject. The mean value of the correlation coefficient for both lower limbs of all subjects was found to be 0.988 and 0.986 for hip and knee angles, respectively at low noise levels. The mean value of MAE with respect to the reference data at low noise levels were 2.1° and 4.51° for hip and knee angles, respectively. The mean values of MAE estimated for each case with different noise levels are listed in Table 6.6 and the correlation values are listed in Table 6.7. Due to the unavoidable errors in the measurements, the target can reach unreachable positions, and this causes oscillations in the system. In this experiment, we used damped least squares to avoid these oscillations. In [13], the author conducted similar experiments with one sensor attached to the torso and the subjects were told to do squat exercise with both feet fixed on the ground. The system proposed in our work allows the movement of both the extreme ends of the system (hip and ankle), and we find the relative motion to find the angle between the limbs. Here, the chances of error will be higher than the case where one end is fixed as the errors in both the markers will contribute to the error in the joint angles.

FIGURE 6.12: The graphs of the knee and hip flexion and extension angles from the proposed method compared with the actual joint angles at lower noise levels.

6.6 Conclusion

In conclusion, spatial multiple access of ultrasonic sensors for tracking multiple mobile nodes can be used to track the bilateral symmetry of human body movements. The narrowband ultrasonic system developed was found to be a cheap and convenient alternative for bilateral symmetry analysis with minimum complexity. It can also be used to extract the gait parameters such as step length, swing time, step width, etc from gait trajectory. The system can be tested for assessing the recovery of patients in clinics and has potential applications in rehabilitation medicine. The proposed SDMA method becomes complex as the number of mobile nodes increases and it cannot be employed if the nodes to be tracked are close to each other making them difficult to separate spatially.

Our simulation results for lower limb joint angle tracking using only two wearable nodes show that the proposed method can track the joint flexion and extension angles with clinical accuracy at low and medium noise levels with slightly lower accuracy for the knee angle at the medium noise level. In the future, the accuracy of the system needs to be checked with two ultrasonic markers attached to the lower limbs.

Chapter 7

Multiple Access and Doppler Correction Using Narrowband Chirp Signals

7.1 Introduction

Gait analysis using cost-effective narrowband ultrasonic transducers demand high accuracy and data update rate along with simultaneous tracking of multiple mobile nodes. In Chapter 6, we discussed the implementation of spatial division for multiple access, where each mobile node should be at a minimum separation to avoid interference. To track mobile nodes which are closer to each other and to reduce the number of mobile nodes, we need some robust channel multiple access methods which require coding the ultrasonic signals which are transmitted from different mobile nodes. For tracking multiple moving ultrasonic nodes, multiple ultrasonic nodes need to emit signals simultaneously in the presence of the Doppler effect, which requires a careful utilization of the available bandwidth. We present two ranging methods using chirp signals for Doppler correction. In [5], a chirp waveform diversity design for static transducers is explained. The signal transmitted by each transmitter was made up of sub-chirps and was optimized for maximum orthogonality. However, moving ultrasonic transducers introduces Doppler shift in the received signals, and this affects not only the orthogonality of individual waveform but also the range measurements extracted. A bank of correlation receivers

is used in many systems to estimate and correct the Doppler shift [167, 168] where the frequency of the transmitted signal is shifted in steps to find the maximum amplitude of the correlation of the transmitted signal with the received signal. These systems are not computationally efficient as a lot of correlation operations need to be performed. A system which uses pilot carriers with a higher transmission power was explained in [165]. Even though this avoids the need for a bank of matched filters, altering a particular frequency component decreases the correlation performance, and we also need higher resolution in the frequency domain to achieve high accuracy tracking. Thus Doppler correction using a pilot carrier (Chapter 4) becomes difficult as the number of active mobile nodes increases. We propose a method for estimation and correction of Doppler effect which does not use a bank of matched filters, instead requires only two correlations for estimating one sample point. The contribution of this chapter is two folds; initially, we propose a method in which more than two ultrasonic signals can be transmitted simultaneously in the presence of Doppler effect. In the second method, a Doppler-velocity estimation algorithm is proposed which successively tracks and adjusts the errors due to the Doppler effect in each sampling point. We exploit the range-Doppler coupling [171] to estimate the Doppler shift and correct the range using the estimated velocity in each step.

7.2 Ranging between mobile and static nodes

An ultrasonic localization system can be designed with an active or passive mobile node architecture. In an active mobile node architecture, the mobile nodes send signals which will be captured by anchor nodes and analyzed for range estimation. For systems with the number of mobile nodes less than or equal to the number of anchor nodes, the active mobile node architecture is desired as the number of simultaneously transmitted signals, and thus the multiple access interference and the power consumption is lower compared to passive mobile node architecture. Also, the data collection in a central server will be easier with active mobile node architecture if wired connections between anchor nodes and a central server are to be employed. This chapter represents the ranging between four mobile nodes and one receiver (see the setup shown in Figure 7.1 in which multiple mobile transmitters are attached on a moving pendulum and the static receiver acquires

FIGURE 7.1: A representation of the setup to measure range from one anchor node to four mobile nodes on a pendulum swinging in the X-Y plane [6].

the signal). The velocity of the moving transmitters with respect to the receivers introduces a Doppler shift in the frequency of the received signals. Let $\hat{S}_n(t)$ be the frequency shifted transmitted signal in time domain corresponding to the originally transmitted signal $S_n(t)$. The received signal at one receiver can be represented by:

$$R(t) = \sum_{n=1}^N \hat{S}_n(t) * I_n(t) + n(t) \quad (7.1)$$

Where, $\hat{S}_n(t)$ represents the Doppler shifted signal transmitted by n^{th} transmitter, $I_n(t)$ represents the impulse response of the ultrasonic channel which accounts for the multi-path components as well and $n(t)$ represents the additive white gaussian noise. For coherent reception and ToF calculation at the anchor nodes, we take the correlation of the transmitted wave with the received signal. The correlation of $R(t)$ with the k^{th} transmitted waveform yields:

$$\begin{aligned} C_k(t) &= \left[\sum_{n=1}^N \hat{S}_n(t) * I_n(t) + n(t) \right] \star S_k(t) \\ &= \left[\hat{S}_k(t) * S_k(-t) \right] * I_k(t) \\ &+ \left[\sum_{n \neq k} \hat{S}_n(t) * S_k(-t) \right] * I_n(t) + n(t) * S_k(-t) \end{aligned} \quad (7.2)$$

Where, $\star$ represents correlation operation and $*$ represents convolution operation. The ToF information is embedded in the first term of Equation (7.2), $\left[\hat{S}_k(t) * S_k(-t) \right] * I_k(t)$. In the absence of Doppler effect, that is when the velocity of the mobile node is zero, this term becomes $\left[S_k(t) * S_k(-t) \right] * I_k(t)$. As velocity increases, the peak amplitude decreases, and the time at which the peak happens

also changes if linearly varying signal frequency is used for ranging. The second term in Equation (7.2) accounts for the multiple access interference. The ToF is estimated from the peak value of $\mathbf{C}_k(t)$ and we convert the ToF to distance by multiplying with the velocity of the wave. The velocity of the ultrasound is given by $v = 331.5 + 0.6 \times T$, where T is the ambient temperature in degree Celsius. We conduct the experiments at 23°C room temperature. The temperature correction can be automated by introducing a temperature sensor in the system, and in that case, we do not require any re-calibration once the system is set up. The dependence of sound velocity on humidity and altitude is negligible.

7.3 Signal Design

Linear chirp sequences are used in the proposed ranging system to obtain good correlation characteristics. Unlike broadband sensors such as EMFi and PVDF narrowband piezoelectric ceramic sensors are cheaper (<USD \$50), lighter and works with low voltage (<20v). However, these sensors have a narrow bandwidth of around 2-4 kHz centered at its resonance frequency. Hence, we selected the narrow bandwidth of 38-42 kHz for our experiments. Sensors with higher bandwidth can provide better results with increased complexity and cost. The narrow bandwidth is more critical for the transmitters as there are commercially available MEMS microphones which can receive broadband signals using low-power; however, transmitters need high DC-bias voltage. Two sets of chirp sequences were created by concatenating linear sub-chirps with same chirp lengths and bandwidths and having different starting and stopping frequencies. The first set contains only sub-chirps with linearly increasing frequencies while the second set contained only sub-chirps with linearly decreasing frequencies. An optimization method was used for selection of the sequence of sub-chirps. The steps for signal design are briefly explained here [5].

7.3.1 Step-1

Linear up and down chirps were generated using the Equation (7.3).

$$\begin{aligned} S_u(t) &= \cos\left\{2\pi\left(f_s t + \frac{(f_e - f_s)t^2}{2 \times T_s}\right)\right\} \quad 0 \leq t \leq T_s \\ S_d(t) &= \cos\left\{2\pi\left(f_e t - \frac{(f_e - f_s)t^2}{2 \times T_s}\right)\right\} \quad 0 \leq t \leq T_s \end{aligned} \quad (7.3)$$

Where, f_s and f_e are starting and ending frequencies and T_s represents the total signal duration.

7.3.2 Step-2

Divide the up and down chirps into N sub-chirps using Equation (7.4).

$$\begin{aligned} Y_{u_n}(t) &= \cos\left\{2\pi\left(f_{s_n} t + \frac{(f_{e_n} - f_{s_n})t^2}{2 \times T_c}\right)\right\} \quad 0 \leq t \leq T_c \\ Y_{d_n}(t) &= \cos\left\{2\pi\left(f_{e_n} t - \frac{(f_{e_n} - f_{s_n})t^2}{2 \times T_c}\right)\right\} \quad 0 \leq t \leq T_c \end{aligned} \quad (7.4)$$

Where, $f_{s_n} = f_s + \frac{(n-1)(f_e - f_s)}{N}$, $f_{e_n} = f_{s_n} + \frac{(f_e - f_s)}{N}$, $n = 1, 2, \dots, N$ and $T_c = \frac{T_s}{N}$. We considered two scenarios: (1) $f_s = 38$ kHz, $f_e = 42$ kHz, $T_s = 12$ ms and $N = 4$ so that each chirp-let stretches 1 kHz in 3 ms time. (2) $f_s = 37$ kHz, $f_e = 43$ kHz, $T_s = 12$ ms and $N = 6$ so that each chirp-let stretches 1 kHz in 2 ms time.

7.3.3 Step-3

Chirp basis signals are created for set-1 (up chirp) and set-2 (down chirp) using Equation (7.5).

$$\begin{aligned} \phi_{n,u}(t) &= \sum_{n=1}^N Y_{u_n}(t - (n-1)T_c) \\ \phi_{n,d}(t) &= \sum_{n=1}^N Y_{d_n}(t - (n-1)T_c) \end{aligned} \quad (7.5)$$

FIGURE 7.2: Representation of (a) up chirp basis and (b) down chirp basis signals for the first scenario. Each colour represents different basis signals.

Figure 7.2 shows the generated up chirp basis and down chirp basis signals.

7.3.4 Step-4

Generate N orthogonal unity height pulses. Construct a randomly circular shifted N unity height pulses which will be optimized using a trial and error method for maximum orthogonality.

$$\eta_{n,i}(t) = U(t) \text{shift}\left((i_n - 1)T_c\right) \quad (7.6)$$

Where, $i_n \in 1, 2, \dots, N$, $\text{shift}(t)$ represents circular shift by t and

$$U(t) = \begin{cases} 1 & 0 \leq t \leq T_c \\ 0 & T_c < t \leq T_s \end{cases}$$

7.3.5 Step-5

Create orthogonal sets of N signals for the up sub-chirps. From the i sets of signals generated, j sets of N orthogonal signals are formed. An optimization algorithm

was carried out to find the set of signals with minimum cross-correlation peak as well as minimum side-lobe peaks for auto-correlation. The maximum peak in the auto-correlation of a signal other than the main peak together with the maximum peak of cross-correlation with other signals in the set was minimized. Here we used an exhaustive search method with 10000 iterations to find the best candidate signal set which gives least multiple access interference when transmitted simultaneously. However, this is only a one-time search and once the set of signals are obtained, the same signals can be used for all the experiments.

$$s_{j,u}(t) = \sum_{n=1}^N \phi_{n,u}(t) \eta_{n,j}(t) \quad (7.7)$$

The value of $\eta_{n,j}(t)$ which provides maximum orthogonality was identified as $\eta_{n,j_{opt}}(t)$. The corresponding down sub-chirp signals are generated by Equation (7.8). Since the sweep directions of the chirp signals do not affect the correlation performance [193], we can use the same optimized set of unity height pulses to generate the set-2 signals using down sub-chirps. The set-1 signals optimized using the iterative optimization algorithm and the corresponding set-2 signals for four ultrasonic transducers are shown in Figure 7.3.

$$s_{j,d}(t) = \sum_{n=1}^N \phi_{n,d}(t) \eta_{n,j_{opt}}(t) \quad (7.8)$$

FIGURE 7.3: (a) Four signals in set-1 after optimization and (b) the corresponding signals in the set-2

7.4 Proposed Method

Once two sets of signals are ready, each transmitter transmits their corresponding signal from each set to calculate the range independently one after the other in each cycle of data acquisition. The total duration of one data acquisition cycle was set to 40 ms, out of which first 20 ms for ranging with the signal from set-1 and next 20 ms for ranging with the corresponding signal from set-2. The timeline for one ranging cycle is shown in Figure 7.4. Two kinds of range-Doppler coupling neutralization (Chapter 4) methods to obtain the accurate range measurements are explained here. From Equation (7.2), it can be seen that the Doppler shift introduces errors in the first (ToF value) and the second terms (multiple access error). The Doppler-effect shifts the frequency of the different transmitted signals in different amounts and this also increases the multiple access error. In the proposed methods, first method corrects only errors in ToF value while the second method estimates the Doppler-velocity and corrects both errors. The proposed methods are explained here:

7.4.1 Mean-measurement method

In this method, we take the average value of the range measurements to remove the range-Doppler coupling effect. In our method, we use coded chirp signals and mean value of signals from set-1 and set-2 are taken as the estimate of actual measurement. The actual range measurements can be estimated by Equation (7.9).

$$\begin{aligned} r_{1n}(t) &= r_{0n}(t) + \frac{\dot{r}_n(t) f_0 T_s}{B} \\ r_{2n}(t) &= r_{0n}(t) - \frac{\dot{r}_n(t) f_0 T_s}{B} \\ r_{0n}(t) &= \frac{(r_{1n}(t) + r_{2n}(t))}{2} \end{aligned} \quad (7.9)$$

Where, $r_{1n}(t)$, $r_{2n}(t)$ and $r_{0n}(t)$ represents the range estimated using signals from set-1, set-2 and the actual range value respectively for the n^{th} mobile node. The Doppler-velocity which is the velocity of mobile node along the line connecting the mobile node and the anchor node is represented by $\dot{r}_n(t)$. Centre frequency, $f_0 = (f_s + f_e)/2$ and bandwidth, $B = f_e - f_s$

FIGURE 7.4: Representation of one ranging cycle [6].

FIGURE 7.5: Flow chart showing the steps involved in the coherent reception during Doppler-velocity correction method [6]

7.4.2 Doppler-velocity correction method

In this method, the Doppler-velocity is estimated from range calculated using signals from set-1 and set-2 in each sampling instance, and the template waveform for correlation at the receiver side is corrected for mismatch of received signals and originally transmitted signals. As the peak value of correlation at the receiver decreases due to the mismatch introduced by the Doppler effect, peaks due to multiple access interference can have higher values when compared to the main peak which leads to large errors in the measured range. Figure 7.5 shows the flow chart for the method we used to compensate these errors during the coherent reception. In each step, the differential Doppler-velocity, $\Delta \dot{r}_n(t)$ can be calculated from Equation (7.9) by subtracting $r_{2n}(t)$ from $r_{1n}(t)$.

$$\Delta \dot{r}_n(t) = [r_{1n}(t) - r_{2n}(t)] \frac{B}{2f_0 T_s} \quad (7.10)$$

At any point, if the estimated Doppler-velocity is above the maximum set Doppler-velocity, V_{dmax} or below the minimum set Doppler-velocity, V_{dmin} , The Doppler-velocity used for correction in the next step is reset to zero. V_{dmax} and V_{dmin} represents the maximum and the minimum Doppler velocity that the moving sensors encounters. This can be set by knowing the maximum relative velocity of the moving transmitters with respect to the receivers. In our experiments, we set V_{dmax} and V_{dmin} as the maximum and minimum velocity that a sensor attached on the lower limb of a person walking at 3 kph on a treadmill may encounter. We kept the value approximately as ± 3 m/s after doing some trials. The template signals for correlation at the receiver are corrected to account for the Doppler effect with the Doppler velocities obtained in previous step. The new chirp signals are generated using Equation (7.11) [172].

$$\begin{aligned}\hat{S}_u(t) &= \cos\left\{2\pi\left(b_n(t)f_s t + \frac{b_n(t)^2(f_e - f_s)t^2}{2 \times T_s}\right)\right\} \\ \hat{S}_d(t) &= \cos\left\{2\pi\left(b_n(t)f_e t - \frac{b_n(t)^2(f_e - f_s)t^2}{2 \times T_s}\right)\right\}\end{aligned}\quad (7.11)$$

Where, $b_n(t) = \frac{v}{(v+v_{d_n}(t-T_s))}$ and $0 \leq t \leq \frac{T_s}{b_n}$. The velocity of sound waves is given by $v = 331.5 + 0.6 \times T$, T is the temperature and $v_d(t - T_s)$ is the estimated Doppler-velocity at the $(n - 1)^{th}$ instance given by Equation (7.12).

$$v_{d_n}(t - T_s) = \sum_{i=0/r_s}^{t-T_s} \Delta \dot{r}_n(i) \quad (7.12)$$

Please note that when v_{d_n} is reset to zero at any point, the sum will be taken from that point, $t = r_s$. After correction, new basis signals are generated and new template signals for correlation are obtained from the already optimized symbols as explained in Section 7.3. Finally, correlation is performed with new signals with both signals from set-1 and set-2 generated from the new chirp waves $\hat{S}_u(t)$ and $\hat{S}_d(t)$. The average value of range estimated from both of them is taken as the final range measurement.

As an example, consider the scenario-1 explained earlier with four transmitters. Let $v_{d_n}(t - 2T_s) = 1$ m/s. At time, t , let the range obtained using signal from set-1, $r_{1_n}(t) = 1.05$ m and from set-2, $r_{2_n}(t) = 1$ m. Then using Equation (7.10), $\Delta \dot{r}_n(t) = 0.208$ m/s and $v_{d_n}(t - T_s) = 1.208$ m/s. The correction factor for chirp signals, $b_n(t) = 0.996$.

FIGURE 7.6: Doppler-velocity simulated for each mobile node

7.5 Simulation Results

A customized ranging environment with four transmitters and one receiver was simulated in Matlab. The transmitters were made to move towards and away from the receiver periodically with velocities increasing linearly from 0 m/s to $+v_{max}$ m/s and then decreasing to $-v_{max}$ m/s. We started the movement of different transmitters at different times with random starting points. The plot of the velocities of four mobile nodes when $v_{max}=1$ m/s are shown in Figure 7.6. The Doppler shifts in the received signals were simulated according to the velocities of the transmitters. The Doppler velocities are approximately the same as the velocities in Figure 7.6 as the movement was simulated in the propagation direction of the wave. The simulated wireless channel was subjected to one multi-path at random positions with a reflection coefficient of 0.4. The minimum separation between the LOS and NLOS was always kept greater than $1/B$ seconds, which is the maximum range resolution for chirp signals to remove errors due to close multi-path components [194]. To evaluate the performance of the ranging methods explained in Section 7.4, we considered two scenarios with four and six number of mobile nodes, as mentioned in Section 7.3. In each case, the simulation was run for 1000 times, and the mean value of error was calculated. All transmitters were made to send the signal assigned to it simultaneously while they are moving. The sampling rate of the system was set to 500000 samples per second. Two SNR levels were considered during simulations: (1) Additive White Gaussian Noise (AWGN) channel with SNR 0 dB, (2) AWGN channel with SNR -5 dB. We studied the ranging accuracy using four different methods where ranging was conducted using (1) only signals with linearly increasing sub-chirps (set-1), (2) only signals with

TABLE 7.1: Mean of Standard deviation of ranging errors (in mm) with only signals from set-1, set-2, mean-measurement method (M-1) and Doppler-velocity correction method (M-2) using four mobile nodes.

Type	Method	Node1	Node2	Node3	Node4
Simulation with 0 dB SNR	Set-1	82.74	83.88	75.13	80.94
	Set-2	83.21	76.20	80.99	80.70
	M-1	28.36	25.39	22.87	27.72
	M-2	15.43	13.21	12.22	14.34
Simulation with -5 dB SNR	Set-1	88.02	88.44	77.60	85.53
	Set-2	87.31	78.99	84.83	83.98
	M-1	35.01	30.82	27.90	33.03
	M-2	18.92	17.31	15.63	17.27

linearly decreasing sub-chirps (set-2), (3) mean-measurement method and (4) with Doppler-velocity correction method. The attenuation of the ultrasonic signal in the air was modeled as $\mathbf{A} = \mathbf{A}_0 e^{-\gamma \times d}$, where $\mathbf{A}$, $\mathbf{A}_0$ and d are the amplitude after attenuation, the originally transmitted amplitude and the distance from transmitter respectively. The attenuation constant γ was set to 0.17 Np/m. The mean values of the standard deviation of range errors for simulations with maximum Doppler-velocity of 1 m/s and four mobile nodes are provided in Table 7.1. We have also repeated the experiments with different coloured noise in the channel instead of white gaussian noise and we didn't observe any significant change in the results. It can be observed that we are able to get less than 20mm accuracy in all the cases using the Doppler-velocity correction method in scenario-1. For scenario-2 with six number of mobile nodes, we repeated the same experiments to quantify the effect of an increase in multiple access interference. The results are provided in Table 7.2. It can be observed that as the number of transmitters increases, the error also increases. The errors using the proposed methods are much lesser than that of using only set-1 or set-2 signals even though the error increased more in the proposed methods when multiple access interference was increased. To find the dependence of error on the maximum simulated Doppler-velocity, we changed the maximum Doppler-velocity in scenario-1 with 0dB SNR. The average number of error in the estimated range exceeding ± 20 mm was plotted against the maximum simulated Doppler-velocity in Figure 7.7. As the velocity is increased, the error in the range measurements using Doppler-velocity correction method increases much slower compared to the mean-measurement method. The velocity

TABLE 7.2: Mean of Standard deviation of ranging errors (in mm) with only signals from set-1, set-2, mean-measurement method (M-1) and Doppler-velocity correction method (M-2) using six mobile nodes.

Type	Method	Node1	Node2	Node3	Node4	Node5	Node6
Simulation with 0 dB SNR	Set-1	114.95	105.74	87.8	82.29	94	88.27
	Set-2	107.71	94.72	87.83	90.49	86.38	69.95
	M-1	71.53	62.93	52.12	51.31	54.4	45.94
	M-2	49.38	38.67	28.79	29.66	26.94	25.95
Simulation with -5 dB SNR	Set-1	131.19	119.91	98.66	94.69	106.07	99.19
	Set-2	122.64	106.77	99.39	103.5	100.64	79.05
	M-1	84.22	73.8	62.35	62.28	65.63	55.1
	M-2	60.59	46.89	36.57	38.68	35.32	32.34

FIGURE 7.7: Percentage of absolute ranging error greater than 20 mm as maximum simulated Doppler-velocity is varied in a wireless channel with 0 dB Gaussian noise

estimated from the Doppler-velocity correction method for one mobile node is compared with the actual velocity in Figure 7.8. It shows that the proposed method can track the Doppler-velocity quite accurately. The plots of the range estimated from signals using set-1, set-2, and Doppler-velocity correction method are shown in Figure 7.9. It can be observed that the range estimated using set-1 and set-2 signals are shifted from the actual range due to the range-Doppler coupling. To summarize, the Doppler-velocity correction method performed better, followed by the mean-measurement method for ultrasonic ranging with four and six number of transmitters using a narrow bandwidth of 4 kHz and 6 kHz respectively.

FIGURE 7.8: Comparison of estimated Doppler-velocity from Doppler-velocity correction method with the actual simulated velocity of one mobile node with 0 dB Gaussian noise for scenario-1.

FIGURE 7.9: The range estimated from the simulation experiment using signals from set-1, set-2 and Doppler-velocity correction method and the actual range at a simulated Doppler-velocity of 1m/s.

7.6 Experimental Procedure

A pendulum experiment was designed to test the proposed method on hardware using narrowband ultrasonic sensors with a center frequency of 40 kHz. We selected MA40S4S and MA40S4R from MURATA as transmitters and receiver respectively. The transmitters and the receiver were connected to NI-USB 6343 Data Acquisition (DAQ) board, which was connected to the PC through USB. DAQ board drives sensors at 10v. Since the sensors used in this experiment work with low voltages ($<20\text{v}$), wireless sensor nodes with ADCs, wireless clock synchronization and batteries can replace this setup to reduce cost without considerable degradation in the ranging performance in the future [7]. Four ultrasonic transmitters were attached on a pendulum with about 120 mm distance between adjacent sensors. The hinge of the pendulum was kept about 1300 mm above the floor level. The

FIGURE 7.10: The pendulum setup with multiple ultrasonic transmitters attached and one static receiver [6].

first, second, third, and the fourth transmitters were placed at a distance of 760, 640, 520 and 400 mm from the hinge. A set of optimized signals from set-1 and set-2 are transmitted through the transmitters attached on a pendulum as shown in Figure 7.10 while the pendulum was made to swing. The ranging was conducted with the receiver placed at eight different positions so that the distance between the pendulum and the receiver lies in between 500 to 1500m. The orientation of the receiver was also changed a little bit each time without affecting the LOS. The experiments were conducted at Motion Analysis Laboratory, Nanyang Technological University, Singapore. Reflective markers of the reference system were placed adjacent to the ultrasonic transmitters and the receiver. The pendulum was released from about 45° from the vertical position after both systems are started. The range measurements were recorded for about 16 seconds. This experiment was repeated eight times and the mean value of the standard deviation between the range values extracted from ultrasonic sensors and the motion capture system was found out. To filter out large errors which lie outside our range, we used a pre-filtering step in which a range measured was considered as a valid measurement only if the range estimated from both set-1 and set-2 corresponding to the sampling point lies in our range of interest.

7.7 Results and Discussions

We aimed to test whether orthogonally coded chirp signals can be used for accurate tracking and simultaneous Doppler correction without using a bank of matched filters at the receiver side for indoor tracking applications. The results from the pendulum experiment are shown in Table 7.3. As expected, both Doppler-velocity correction method and the mean-measurement method resulted in an improvement in the standard deviation between the proposed ranging system and the Motion capture system when compared to the results obtained from only set-1 or only set-2. The improvement in tracking performance is narrow as the Doppler-velocity experienced by the ultrasonic sensors during the pendulum experiment is very small, this is because the major part of movement happens in a direction perpendicular to the transmission direction of the ultrasonic wave. The range measurements obtained from the ultrasonic system using the proposed method and the motion capture system are compared in Figure 7.11. The proposed method can be used to offset the errors brought about by the movement of mobile nodes in ultrasonic localization systems. Unlike accelerometers and gyroscopes, we do not need any integration to find the three-dimensional position for localization using ultrasonic ranging and hence the localization systems using this method can be exploited for long-duration tracking of moving targets. From the simulation results, we can find that the error does not increase much using Doppler-velocity correction method as the maximum Doppler-velocity was increased from 0.25 to 2 m/s. In both methods, two number of correlations need to be conducted to estimate one sample point. The second method also includes calculation of Doppler-velocity, which is not computationally intensive compared to the complexity of a bank of matched filters [168, 172] where more than two correlations need to be conducted to estimate one sample point. We compare the complexity with earlier methods by counting the number of correlations required. Please note that we are only comparing the complexity at the receiver node and not in the signal design phase. Both the methods in this chapter require only two correlations per sample measurement; however, the bank of correlation receivers requires more than two correlations per sample measurement to remove the Doppler shift. In this chapter, we have tested two methods; mean measurement method is computationally less complex than Doppler-velocity compensation method as the latter requires correction of correlation waveform according to the estimated Doppler velocities in each ranging cycle.

TABLE 7.3: The mean value of the Standard deviation of ranging errors (in mm) with only signals from set-1, set-2, mean-measurement method (M-1) and Doppler-velocity correction method (M-2) during the pendulum experiment

Method	Node1	Node2	Node3	Node4
Set-1	5.70	6.10	4.16	3.69
Set-2	6.19	6.09	3.83	3.69
M-1	5.68	5.08	3.74	3.39
M-2	5.69	5.04	3.74	3.39

FIGURE 7.11: Comparison of Range measurements from the camera system and the ultrasonic system with the proposed method during the pendulum experiment.

In each ranging cycle of Doppler-velocity compensation method, we need to implement Equations 7.10, 7.11, and 7.12 in addition to two correlations of mean measurement method at the receiver side. The maximum Doppler-velocity and the capture volume have limitations in this system. The range of ultrasonic sensors used was 0.2 to 4 m. In the simulation experiments, we subjected the sensors to a maximum Doppler-velocity of 1 m/s and a multi-path reflection with a reflection coefficient of 0.4, and we observed good tracking performance. However, the maximum Doppler-velocity, the system can withstand, depends on the multi-path effect, the number of transmitters, and the available bandwidth. In our experiments with sensors, we subjected small Doppler velocities less than 0.5 m/s as the movement was parallel to the receivers for maintaining LOS. In our experiments, the distances between different ultrasonic transducers are not very large, and thus we did not face near-far effect ([115, 195]), as the nodes were facing each other and the distance between them was small. This problem, along with higher Doppler velocities, needs to be tested in the future. The Doppler-velocity compensation method is slightly complex compared to the mean-measurement method as the correlation waveform need to be corrected with respect to estimated Doppler-velocity in each measurement cycle.

7.8 Conclusion

Two methods for ultrasonic ranging between multiple slow-moving ultrasonic transducers with Doppler shift compensation are proposed. Orthogonally coded linearly increasing and decreasing chirp signals were employed for ranging. Simulation results show that the proposed method can enhance the performance of small-scale ultrasonic ranging. The Doppler-velocity compensation method outperformed the mean-measurement method in the simulation results as the former accounts for the modification of linear chirp by the Doppler effect. A pendulum experiment was conducted using narrowband ultrasonic sensors, and we obtained an improvement of about 1 mm in the standard deviation of ranging errors at lower moving velocities using the proposed methods, Mean-measurement and Doppler velocity correction methods compared to only set-1 or set-2 signals. This system can find applications in motion tracking, such as gait analysis. However, the effects of changes in multipath conditions, the near-far effect on the ranging performance need to be studied in detail. Eventhough, Doppler-velocity compensation method performed well, it is slightly complex compared to the mean-measurement method. Hence, we select mean-measurement method for our gait analysis system in wireless sensor nodes.

Chapter 8

Bilateral Gait Analysis Using Chirp Division Multiple Access and Doppler Correction

8.1 Introduction

In this chapter, we implement the mean-measurement method explained in Chapter 7 in the wearable wireless nodes for bilateral gait analysis with two wearable nodes. The effective utilization of the bandwidth of narrowband ultrasonic sensors for multiple access and Doppler correction in a wearable gait analysis system is discussed. In Chapter 3, we found that wearable ultrasonic sensors gave better tracking accuracy compared to UWB sensors for gait analysis. Chapters 4 discusses two methods of Doppler shift compensation and selected range-Doppler coupling compensation method for further analysis as this method gave better tracking accuracy. In Chapter 5, we explained a method for close multipath component compensation with limited bandwidth and implemented in a gait analysis system with one wearable node. The use of this method was limited to one mobile node and hence we did not consider the method for bilateral gait analysis. Chapter 6 describes spatial division multiple access for ultrasonic channel multiple access in a bilateral gait analysis system. Since the spatial separation of close targets are difficult and we need more number of nodes in spatial division multiple access, we introduced orthogonal coded chirps for simultaneous multiple access and

Doppler-shift compensation for more than two mobile targets in Chapter 7. Two methods were proposed and tested with a pendulum experiment using four mobile nodes. Even though the Doppler-velocity compensation method performed better, we adapt mean-measurement method explained in Chapter 7 as it is slightly less complex compared to Doppler-velocity compensation method and gives satisfactory performance for ranging. As discussed in earlier chapters, the distances of the mobile nodes whose coordinates, are to be estimated from three or more anchor nodes with known coordinates, are required for localization. These distances are calculated from the time the ultrasonic waves takes to travel from mobile nodes to anchor nodes or vice versa. For human motion tracking, we prefer active mobile node architecture. Let the coordinates of the mobile node be $(\mathbf{x}, \mathbf{y}, \mathbf{z})$ and that of the i^{th} anchor node be $(\mathbf{x}_i, \mathbf{y}_i, \mathbf{z}_i)$, then the estimate of range, $\mathbf{d}_i$ can be expressed as

$$\mathbf{d}_i = (\mathbf{x}_i - \mathbf{x})^2 + (\mathbf{y}_i - \mathbf{y})^2 + (\mathbf{z}_i - \mathbf{z})^2 + \mathbf{n}_i \quad (8.1)$$

Where, $\mathbf{n}_i$ is the measurement noise and $i=1,2,..m$, where $m \geq 3$. Equation (8.1) can be solved for $(\mathbf{x}, \mathbf{y}, \mathbf{z})$ using some iterative algorithms such as least squares estimation [87], Kalman filter [30] or a particle filter [196].

We use the mean-measurement method explained in Chapter 7 for simultaneous Doppler correction and channel multiple access and implement the system with wireless sensors so that bilateral gait analysis can be enabled with two wearable mobile nodes and four anchor nodes. We do not need to code chirp signals with codes here as we need only two mobile nodes.

8.2 Description of Problem

Let the number of mobile nodes transmitting ultrasonic waves simultaneously be N . The signal transmitted by each mobile can be represented by $\mathbf{S}_i$ where $i=1,2..N$. The signal received by one receiver in the absence of multi-path effect can be represented as [102]:

$$\mathbf{R}(t) = \sum_{i=1}^N \mathbf{A}_i \times (\mathbf{h}_i * \mathbf{S}_i)(t - t_i) + \mathbf{n}(t) \quad (8.2)$$

Where, $\mathbf{A}_i$ and $\mathbf{t}_i$ are the amplitude and time of flight of the signal received from i^{th} transmitter. $\mathbf{h}(\mathbf{t})$, $\mathbf{n}(\mathbf{t})$ and $*$ represent channel impulse response, additive white Gaussian noise (AWGN) and the convolution operator. However, Equation (8.2) takes into account only the direct signal path. In an indoor environment, multiple delayed and attenuated replicas of the transmitted signals are also received due to the reflections from nearby surfaces. The received signal from i^{th} transmitter can be modeled as shown in Equation (8.3).

$$\mathbf{A}_i \times (\mathbf{h}_i * \mathbf{S}_i)(\mathbf{t}) \approx \sum_{m=1}^M \mathbf{A}_{im} \times \mathbf{S}_i(\mathbf{t} - \mathbf{t}_m) \quad (8.3)$$

Where, M is the number of multi-path components received for i^{th} signal and $\mathbf{t}_m = \mathbf{t}_i + \Delta\mathbf{t}_{im}$ where $\Delta\mathbf{t}_{im} = \mathbf{0}$ for the direct path without reflections. After reception, $\mathbf{R}(\mathbf{t})$ is correlated with a locally stored copy of emitted signal, $\mathbf{S}_k$. The waveform after correlation with k^{th} waveform can be represented as [102]:

$$\begin{aligned} \mathbf{C}_k(\mathbf{t}) &= \left(\sum_{i=1}^N \mathbf{A}_i \times (\mathbf{h}_i * \mathbf{S}_i)(\mathbf{t} - \mathbf{t}_i) + \mathbf{n}(\mathbf{t}) \right) \star \mathbf{S}_k(\mathbf{t}) \\ &= \left(\sum_{m=1}^M \mathbf{A}_{km} \times \mathbf{S}_k(\mathbf{t} - (\mathbf{t}_k + \Delta\mathbf{t}_{km})) \right) \star \mathbf{S}_k(\mathbf{t}) \\ &+ \left(\sum_{i \neq k} \sum_{m=1}^M \mathbf{A}_{im} \times \mathbf{S}_i(\mathbf{t} - (\mathbf{t}_i + \Delta\mathbf{t}_{im})) + \mathbf{n}(\mathbf{t}) \right) \star \mathbf{S}_k(\mathbf{t}) \end{aligned} \quad (8.4)$$

In Equation (8.4), the first term on the right-hand side is the auto-correlation of transmitted signal distorted by the multi-path interference. The distance information from k^{th} transmitter is embedded in $\mathbf{t}_k$. The second term on the right-hand side represents the multiple access interference and the channel noise. Index of the peak value of $\mathbf{C}_k(\mathbf{t})$ can be used to estimate $\mathbf{t}_k$. Equation (8.4) is applicable for stationary transmitter and receiver. However, if the transmitter is moving relative to the receivers, the frequency of the received signal, $\mathbf{S}_i$ is shifted up or down proportional to the velocity due to the Doppler shift. The errors introduced by the Doppler effect in the range measurement depends on the signal design. We use chirp signals with linearly varying frequency. Let $\mathbf{S}_i(\mathbf{t})$ represents a linear chirp signal with the frequency varying from $\mathbf{f}_1$ to $\mathbf{f}_2$ in time $\mathbf{T}_s$. Let the relative velocity between the ultrasonic transmitter and the receiver be $\mathbf{v}_r$ with transmitter moving away from the receiver. Then the expansion or compression factor of the received

signal, $\mathbf{b}$ can be obtained as shown in Equation (8.5).

$$\mathbf{b} = \frac{\mathbf{c}}{\mathbf{c} + \mathbf{v}_r} \quad (8.5)$$

Where, $\mathbf{c}$ is the velocity of ultrasound in air. The received signal after Doppler shift will be a chirp signal with the frequency varying from $\mathbf{bf}_1$ to $\mathbf{bf}_2$ in time $\mathbf{T}_s/\mathbf{b}$ [172]. The estimated time delay, $\mathbf{t}$ in the received signal will be a linear function of the frequency [171].

$$\mathbf{t} = \mathbf{t}_0 - \frac{\mathbf{T}_s}{(\mathbf{f}_2 - \mathbf{f}_1)} \times \mathbf{f} \quad (8.6)$$

Let the frequency shift due to Doppler shift be $\Delta \mathbf{f}$ and error in estimated time be $\Delta \mathbf{t}$. Then,

$$\Delta \mathbf{t} = \frac{-\mathbf{T}_s}{(\mathbf{f}_2 - \mathbf{f}_1)} \times \Delta \mathbf{f} \quad (8.7)$$

which is a function of the velocity of moving target as the frequency shift is proportional to the relative velocity for a particular chirp signal.

8.3 Proposed Method

Various methods to reduce multiple access interference using chirp signals are explained in [102]; however, the effect of mobile node movement on continuous measurement accuracy and Doppler effect compensation are not taken into account. In our experiments, two mobile nodes are attached to the left and right lower limbs of the subject whose gait patterns are to be analyzed. In Chapter 6, a similar gait analysis model was explained. However, spatial division multiple access was utilized with two separate boards with four fixed anchor nodes on either side of the body enabling simultaneous transmission of two mobile nodes. Here, the two boards need to be synchronized, and the positions of all the sensors need to be known without error. The limited transmission angle was taken advantage here for multiple access. Two mobile nodes close to each other cannot transmit at the same time due to interference in such systems. To avoid errors due to Non-Line of Sight (NLOS), we need to increase the transmission angle of the sensors, and this makes spatial division multiple access difficult. This is because the range estimation is prone to interference as multiple mobile nodes are transmitting the same waveform, which also affects the scalability of the system for more than two

mobile nodes. In this chapter, we test two methods for multiple access, along with a Doppler compensation technique for moving targets. The multiple access performance with more than two narrowband ultrasonic sensors with 40 kHz center frequency transmitting simultaneously was explained in [102, 115]. However, the performance when the targets are moving was not studied. The methods for simultaneous multiple access and Doppler shift correction had been discussed in Chapter 7. In this work, we are investigating the multiple access performance of two ultrasonic mobile nodes in static condition as well as in dynamic condition when the system is used for bilateral gait analysis.

8.3.1 Signal Design

In this work, we test two designs for the transmitted signal to minimize multiple access interference. In the first design, the rate of variation of chirp frequency is used to identify the mobile node from the transmitted signal [115]. That is one signal's frequency linearly increases at the same time, the frequency of the other signal linearly decreases. In the second design, the orthogonality of the discrete frequency components of a chirp waveform was utilized for positioning two transducers simultaneously [115]. In the second design, the length of the signal is doubled, and thus the computational cost also increases as the number of mobile nodes increase.

8.3.1.1 Up- and Down-Chirp for Multiple Access

A linear chirp can be mathematically represented as:

$$S_i(t) = \text{rect}\left(\frac{t}{T_s}\right) \times \exp\left\{j2\pi\left(f_{si}t + \frac{1}{2}u_i t^2\right) + \phi\right\} \quad (8.8)$$

Here, $\text{rect}(\cdot)$ represents a rectangular window function. T_s is the chirp signal duration. f_{si} is the starting frequency, ϕ is the initial phase and is set to zero. $u_i = (f_{ei} - f_{si})/T_s$ where f_{si} and f_{ei} are starting and ending frequencies respectively. The two signals required for our system are generated utilizing the additional degree of freedom for modulation compared with single tone signals. That is the chirp rate [198]. Let S_1 and S_2 be the signals ($i=1,2$), then for S_1 , $f_{s1}=39$ kHz, $f_{e1}=41$

FIGURE 8.1: Illustration of up- and down-chirp rates for two signals with 39-41 kHz/9 ms chirp waveform

kHz, $u_1 > 0$ and for S_2 , $f_{s2}=41$ kHz, $f_{e2}=39$ kHz, $u_2 < 0$. An illustration of the chirp signals used is shown in Figure 8.1

8.3.1.2 Orthogonal Frequency Division Multiple Access

In the second method, the orthogonality of discrete frequency components of the signals is utilized. Here we are using orthogonal chirp signals. Since we are having only two sets of ultrasonic transmitters transmitting simultaneously, we used a simple technique to generate the signals. In the time domain, the first up-chirp signal generated in Equation (8.8) is concatenated in the time domain with itself to get the first waveform. The second waveform is obtained by concatenating the negative of the up-chirp signal with itself in the time domain. Let $\mathbf{T}\mathbf{x}1$ and $\mathbf{T}\mathbf{x}2$ represent the two orthogonal signals to be generated and $\mathbf{S}_1(t)$ represents the up-chirp signal with signal duration $T_s/2$. Then,

$$\begin{aligned} \mathbf{T}\mathbf{x}1 &= \text{rect}\left(\frac{t}{T_s/2}\right) \mathbf{S}_1(t) + \text{rect}\left(\frac{t - T_s/2}{T_s/2}\right) \mathbf{S}_1(t - T_s/2) \\ \mathbf{T}\mathbf{x}2 &= \text{rect}\left(\frac{t}{T_s/2}\right) \mathbf{S}_1(t) - \text{rect}\left(\frac{t - T_s/2}{T_s/2}\right) \mathbf{S}_1(t - T_s/2) \end{aligned} \quad (8.9)$$

In the frequency domain, this operation corresponds to zero interleaving Discrete Fourier Transform (DFT) of $\mathbf{S}_1$ to obtain frequency domain equivalent of $\mathbf{T}\mathbf{x}1$ and shifting the frequency domain equivalent of $\mathbf{T}\mathbf{x}1$ by one position to the right to get the frequency domain equivalent of $\mathbf{T}\mathbf{x}2$ [86]. Although both signals, $\mathbf{T}\mathbf{x}1$ and $\mathbf{T}\mathbf{x}2$ are transmitted simultaneously from different transmitters, both signals

FIGURE 8.2: Comparison of (a) auto-correlation and (b) cross-correlation of S_1 and S_2 for up- and down-chirp signals and (c) auto correlation and (d) cross-correlation of $Tx1$ and $Tx2$ for orthogonal chirp signals

are received by the receiver without much interference as the multiplication of the frequency spectra of both results in zero. The auto-correlation of S_1 , cross-correlation of S_1 and S_2 , auto-correlation of $Tx1$ and cross-correlation of $Tx1$ and $Tx2$ and are provided in Figure 8.2

8.3.2 Doppler Shift Compensation

Moving targets emitting ultrasonic waves lead to Doppler shift in the frequency of the signal received at the stationary receivers. This leads to large errors in the range values estimated. If orthogonal chirp signals are used as explained in Section 8.3.1.2, the Doppler shift can cause the signals to lose orthogonality and the multiple access cannot be possible, especially in this case as the bandwidth is limited. Linear frequency modulated signals are highly tolerant to Doppler effect [199]. In the case of linear chirp signals, the multiple access is rarely affected by the Doppler effect, but an error is introduced in the range measurement which is proportional to the velocity of moving target known as range-Doppler coupling [171]. This error will be positive or negative depending on whether we are using up- or down-chirp. We propose the use of linear chirp signals with positive and negative chirp rates of same magnitude to compensate for range-Doppler coupling similar to the method explained in Chapter 4 and 7. The range value estimated from the up-chirp and down-chirp can be represented as shown in Equation (8.10)

[171].

$$\begin{aligned} \mathbf{r1} &= \mathbf{r0} + \dot{\mathbf{r}} \times T_d \quad \text{for} \quad \text{up-chirp} \\ \mathbf{r2} &= \mathbf{r0} - \dot{\mathbf{r}} \times T_d \quad \text{for} \quad \text{down-chirp} \end{aligned} \quad (8.10)$$

Where, $\mathbf{r0}$ represents the actual range, $\mathbf{r1}$ and $\mathbf{r2}$ represents the estimated range by sending up- and down-chirp signals and $\dot{\mathbf{r}}$ represents the target velocity in the ranging direction. T_d is given by Equation (8.11).

$$T_d = f_0 \times T_s / B \quad (8.11)$$

Where, f_0 is the centre frequency, T_s is the signal duration and B is the swept bandwidth of the chirp signal. The mean value of $\mathbf{r1}$ and $\mathbf{r2}$ gives an estimate of $\mathbf{r0}$.

As an example, Let $f_0=40$ kHz, $T_s=7$ ms and $B=2$ kHz, Then $T_d=0.14$ s. Let us assume that the target is moving at a velocity, $\dot{\mathbf{r}}=1$ m/s away from the receiver and the actual range, $\mathbf{r0} = 1\mathbf{m}$, then, $\mathbf{r1} = 1.14\mathbf{m}$ and $\mathbf{r2} = 0.86\mathbf{m}$. The mean value of $\mathbf{r1}$ and $\mathbf{r2}$ gives us the actual range.

For gait analysis with ultrasonic transmitters attached to the lower limbs of the subject, the velocity of the lower limbs can be few meters per second and thus the range-Doppler coupling causes errors which cannot be tolerated for narrowband signals with the 40 kHz center frequency. Hence, we used two ranging cycles, one with up-chirp, (39-41 kHz)/7 ms and other with down-chirp, (41-39 kHz)/7 ms. Each ranging takes 20 ms, and the mean value is taken as one measurement. After each ranging cycle of 20 ms, we estimate one data point from the average value of alternate chirps from the previous and the next ranging cycle. Thus, the total data update rate of the system is 50Hz.

8.4 Experimental Procedure

Each mobile node consists of one STM32F4-Discovery development board from ST Microelectronics. The chirp waveform to be transmitted is stored inside the flash memory of the STM32F407VGT6 microcontroller at the core of the development board. This board has Direct Memory Access (DMA) controllers, which can enable

FIGURE 8.3: The circuit diagram for the band-pass filter and the amplifier for the received signal

high performance and ultra-fast data transfer to the Digital to Analog Converter (DAC). We used sine chirp waveform from DAC as input to the driver circuit which consists of SN74AS04 hex inverters and IC-SN754410 which can boost the transmission power of the DAC output and can provide a bidirectional current drive of up to 1 A. The driver circuit was similar to the circuit explained in [200]. MURATA MA40S4S and MA40S4R were used as ultrasonic transmitters and receivers respectively. The typical directivity of these sensors is 80 degrees. Both IC-SN754410 and the STM32F4 control board were powered by an 11.1V lithium-polymer battery and a 5V rectifier. At the receiver side, the signal from the ultrasonic receiver was passed through a band-pass filter and amplifier. The received signal was sent through a second-order band-pass filter and an amplifier. The lower and upper cut off frequencies of the band-pass filter were approximately 33 and 48kHz. An inverting op-amp amplifier with a voltage gain of 11 was used. IC-LMV-358 was employed to design the band-pass filter and the amplifier, as shown in Figure 8.3. NI-USB 6343 DAQ board was used to capture the signal which is connected to a PC through a USB connection. The cross-correlation and further analysis were performed in Matlab. The trigger signal from the data acquisition board is transmitted to the mobile node through the STM32F4 board and a wireless transceiver for each ranging cycle. This signal acts as the clock synchronization signal between the ultrasonic transmitter and the receiver. The automatic acknowledgment and re-transmission features of the wireless transceivers were disabled to avoid any

timing delays or jitters in the trigger signal.

8.4.1 Channel Multiple Access

We investigated the performance of the ranging system under multiple access interference with two transmitters in static conditions emitting ultrasonic waves simultaneously. The experimental setup included two transmitters and one receiver. For both signals explained in Section 8.3.1, measurements were taken for ten different locations of the two transmitters with respect to the receiver. Here the clock synchronization between the transmitters and the receiver was done using NRF24L01 Radiofrequency (RF) modules. Block diagrams of the ultrasonic transmitter and receiver circuits are as shown in Figure 8.4 and Figure 8.5 respectively. The DAQ board initiated each measurement cycle by starting to receive from the analog input channel and simultaneously sending the trigger signal to all the mobile nodes through wireless radio frequency connection. The respective chirp signals stored in the memory of the mobile nodes are sent through the ultrasonic transmitters as soon as the mobile nodes receive the trigger signal. At the anchor nodes, the received ultrasonic signal is a combination of transmitted waveform shifted by the corresponding propagation delays, the multiple access interference, and channel noise. The environment in which the experiments were conducted was found to be of less multi-path interference; hence we used simple earliest peak detection method to compensate for the multi-path effect. The multi-path compensation method proposed in Chapter 5 was not used in this experiment as the half-peak detection method might not give good results in presence of multiple access interference. Cross-correlation with the corresponding transmitted waveform and finding the index of the earliest peak value of the envelope of cross-correlation, we obtain the propagation delay of the ultrasonic signals from each mobile node. The distance between the mobile node and the anchor node is obtained by substituting the value of propagation delay in Equation (4.1). The room temperature was assumed as constant and 23°C in this experiment. Figure 8.6 shows the experimental setup used for studying the multiple access performance. The clock synchronization was implemented by a 2.4 GHz wireless connection between the mobile nodes and the anchor nodes.

FIGURE 8.4: Block diagram of ultrasonic transmitter circuit (Mobile node) [7].

FIGURE 8.5: Block diagram of ultrasonic receiver circuit [7].

FIGURE 8.6: The experimental setup to study the multiple access performance [7].

8.4.2 Gait Tracking with the Proposed System

A gait analysis system was proposed with the multiple access localization method by attaching the mobile nodes to each foot of the human subjects facing backward. The performance of the proposed gait analysis system was tested in an indoor environment with the subject walking on a treadmill. Five healthy subjects (4 Males and 1 Female) with age (25.6 ± 0.55) were recruited for the experiment. All the subjects gave their informed consents to participate in the gait experiments. The experiments were conducted at the Motion Analysis Laboratory, School of Mechanical and Aerospace Engineering, NTU, Singapore. All the subjects involved in the experiment had a normal gait without any disorders which affect gait. Ultrasonic sensors with battery and camera markers were attached to each lower limb of the subject with Velcro tape and double-sided tape so that the camera marker and ultrasonic transducers are positioned just above the ankle joint facing backwards as shown in the Figure 8.7. Each subject was asked to walk on a treadmill at fixed walking speeds of 1, 2, and 3 kph each 1 minute each with about 1-minute break in between the trials. One subject was asked to repeat the gait experiment with a simulated leg length discrepancy of 50 mm in the right leg to study the relation of bilateral gait symmetry with leg length discrepancy. The Ultrasonic and Motion capture systems were started at the same time and slight time difference between the systems was offset during post-processing by finding the point at which the cross-correlation between the signals reaches a maximum value. Two mobile nodes with ultrasonic transmitters were attached to either foot of the subject, and four anchor nodes were placed at fixed positions with known coordinates behind the subject as shown in Figure 8.7. The anchor nodes were placed at the corners of a 200×250 mm square, and hence the 3D coordinates of the anchor nodes were set to (0,0,0), (200,0,0), (200,0,250) and (0,0,250). The four anchor nodes were placed about 600 mm above the ground to avoid one leg to interfere with the Line of Sight (LOS) of the other during gait. In the 3D coordinate system, the walking direction was set as -Y, vertical direction as Z and lateral direction as X. The two mobile nodes were programmed to transmit at the same time using the multiple access technique explained in Section 8.3.1.1. One mobile node was made to transmit an up-chirp, (39-41 kHz)/7 ms at the rising edge of the clock signal and a down-chirp, (41-39 kHz)/7 ms at the falling edge of the clock signal. The second mobile node was made to transmit down-chirp at the rising edge of the clock signal and

FIGURE 8.7: The setup for gait tracking with sensors attached to both lower limbs of the subject [7].

FIGURE 8.8: Representation of signals transmitted in one sampling instance of 40ms [7].

up-chirp at the falling edge of the clock signal. One instance of range measurement is as shown in Figure 8.8. We neglected the slight changes in the velocity at which the up- and down-chirps are transmitted, which are 20 ms apart. The clock signal, which was of frequency 25 Hz, was transmitted through wireless radio frequency connection from the DAQ to each mobile nodes. The commands to start the measurements were given from the PC which was connected to the anchor nodes. Since we were using four analog input channels from the DAQ board, the effective sample rate in each channel was set to 125000 samples/s. The signals from four ultrasonic receivers were passed through band-pass filters and amplifiers before sending to the PC through a serial connection. The time taken by the waves to reach each of the four anchor nodes is estimated by cross-correlation of the received wave with the originally transmitted waveform. The mean value of time estimated from up- and down-chirps was taken to remove the Doppler effect. The distances from each mobile nodes to four anchor nodes were calculated using Equation (4.1) at 23°C.

All the distance measurements were passed through a median filter of order 3 to remove some NLOS errors and samples which lie outside the set upper and lower limits were removed. From eight distance measurements thus obtained, a UKF was implemented to estimate the 3D coordinates of both mobile nodes attached to each foot of the subject. As the experiments were conducted in a low multi-path environment the earliest peak, which is not less than 0.8 times the maximum peak was found to provide good results for the multi-path effect. The system model for obtaining the 3D coordinates from the ranges had been explained in Chapter 3.

8.5 Bilateral Gait Analysis and Gait Deviation

A simple symmetry measure was given by $\mathbf{X}_r/\mathbf{X}_l$, where $\mathbf{X}_r$ and $\mathbf{X}_l$ represents the parameters of right and left limbs [201]. *Yogev et. al* explained gait asymmetry as $100 \times |\ln(\mathbf{SR}/\mathbf{SL})|$, where $\mathbf{SR}$ and $\mathbf{SL}$ are the average swing times of right and left lower limbs [123]. Other measures included $100 \times (\mathbf{X}_r - \mathbf{X}_l)/0.5 \times (\mathbf{X}_r + \mathbf{X}_l)$ and $100 \times (\mathbf{X}_r - \mathbf{X}_l)/\max(\mathbf{X}_r, \mathbf{X}_l)$ [201]. Statistical methods for obtaining symmetry index include principal component analysis [202] and correlation coefficients. These methods use a single parameter or a limited number of parameters from the actual waveform.

8.5.1 A New Gait Deviation Measure

We attached two markers on each lower limbs at points equidistant from the sagittal plane. The three-dimensional coordinates of both mobile nodes were recorded using the ultrasonic system and the motion capture system. Initially, the phase differences between the trajectories were obtained from the left and right lower limbs. The phase difference between both was removed and the mean absolute error along y-direction was calculated from the phase-corrected trajectories of the left and right lower limbs. The mean value of the base of gait was also calculated as explained in Chapter 3.

8.5.1.1 Phase Difference Between Limbs

For a normal gait pattern, the phase difference between the trajectories of the left and the right limbs should be around 180° . *Plotnik et al.* described a method to quantify the phase coordination and find the phase difference between the limbs [203]. However, force signals were used to find the heel-strike and toe-off points. This measure does not provide much information about the asymmetry between the trajectories of right and left limbs as the data from sensors are available only when the foot is in contact with the ground. In our method, we are using a wearable ultrasonic tracker to get the 3D trajectories of both limbs and a gait deviation measure is derived. The calculation of gait deviation measure from the three-dimensional trajectories is explained here. Let $(\mathbf{x}_l(t), \mathbf{y}_l(t), \mathbf{z}_l(t))$ and $(\mathbf{x}_r(t), \mathbf{y}_r(t), \mathbf{z}_r(t))$ be the coordinates of left and right lower limbs extracted for a duration of T seconds.

8.5.1.2 Steps for Estimation of Phase Difference

- Identify the limb with higher mean swing time as the reference limb. Let us assume that the right limb is the reference here.
- Find the auto-correlation of the y-coordinate of reference limb, $\mathbf{A}_c(t)$ and the cross-correlation of y-coordinate of reference limb with that of the other limb, $\mathbf{C}_c(t)$. The correlation was done with a maximum delay of -1000 to +1000 samples, which accounts for about eight to ten strides in our system.

$$\begin{aligned}\mathbf{A}_c(t) &= \mathbf{y}_r(t) \star \mathbf{y}_r(t) \\ \mathbf{C}_c(t) &= \mathbf{y}_r(t) \star \mathbf{y}_l(t)\end{aligned}\tag{8.12}$$

Where $\star$ represents the unbiased correlation operation with maximum delay of 1000 samples.

- Find the phase difference between $\mathbf{A}_c(t)$ and $\mathbf{C}_c(t)$.

$$\phi_i = 360 \times \frac{\max_i(\mathbf{A}_c(t)) - \max_i(\mathbf{C}_c(t))}{\max_{i+1}(\mathbf{A}_c(t)) - \max_i(\mathbf{A}_c(t))}\tag{8.13}$$

Where ϕ_i and $\max i(.)$ represents the phase at i^{th} peak and time at which the maximum value peak corresponding to the i^{th} peak happens.

- Find the mean value of ϕ_i

$$\phi = \frac{\sum_{i=1}^N \phi_i}{N} \quad (8.14)$$

Where N is the total number of peaks considered.

8.5.1.3 Removal of Phase Difference Between Limbs

We shift the three-dimensional coordinates of the reference limb an angle corresponding to ϕ in the time domain so that coordinates of both limbs match. The amount of time shift, τ is given by

$$\tau = CT_r \times \frac{\phi}{360} \quad (8.15)$$

Where CT_r represents the average cycle time of the reference limb. The trajectories after time shift is given as $(x_l(t), y_l(t), z_l(t))$ and $(x_r(t-\tau), y_r(t-\tau), z_r(t-\tau))$. The mean absolute error between the new trajectories along y-coordinate (horizontal) is estimated and divided by the mean step length to calculate the bilateral gait deviation measure along the walking direction. A correction factor (SD_s) is introduced in the numerator to avoid the sensor errors in the measurement.

$$BGD_y = \frac{MAE(y_r(t-\tau) - y_l(t)) - SD_s}{0.5 \times (SL_r + SL_l)} \quad (8.16)$$

Where, SL_r and SL_l are the mean step lengths extracted from the trajectory of y-coordinates of right and left limbs and SD_s represents the standard deviation of static measurements for the sensors used. For the proposed system, we set it as 8.4 mm and for the camera system this value will be negligible. It acts as a correction factor for the error contribution by the sensors.

8.6 Results and Discussions

We conducted experiments to find the best-case ranging accuracy for one transmitter and one receiver followed by an experiment with two transmitters and one receiver to study the effect of multiple access interference. For moving targets,

various factors need to be taken care of such as the Doppler shift, the transmission patterns of the ultrasound and the angle between the axis of transmitter and receiver, which depend on the applications. Hence, we tested our system with healthy subjects walking on a treadmill.

8.6.1 Performance in Environments with Multiple Access Interference

Initially, we evaluated the best-case ranging accuracy with one transmitter and one receiver in the absence of multiple access interference and with wireless clock synchronization between the transmitter and receiver. Here, both transmitter and the receiver were in static condition. Eight different range values were measured. The constant offset value was removed, and the error compared with the camera system was found to be -8.51 ± 6.77 mm (Mean $\pm$ Standard Deviation). The constant offset in the measurement can be due to various reasons such as the time taken by RF signal to reach the anchor nodes, the frequency variations due to the non-linear impulse response of the ultrasonic transceivers, etc. The frequency variation leads to received signal not matching perfectly with the transmitted wave, and thus the peak of the correlation might be shifted by a constant offset. To study the performance with multiple access interference, we employed the experimental setup explained in Section 8.4.1 with two static transmitters and one static receiver. One transmitter was made to transmit linearly varying up-chirp and the other was made to transmit down-chirp of length 9 ms (39-41 kHz/9 ms and 41-39 kHz/9 ms) at the same time. Measurements were taken for static conditions at different positions of mobile nodes with respect to one anchor node. Ten continuous measurements were taken every 100 ms for each of the ten different positions of the two mobile nodes. As there was a constant offset in the measurements, we compared the change in the measured distance value with the camera reference system. We subtracted the first set of distance measurements from the rest. The error in range values estimated from the ultrasonic and motion capture system was found to be 10.54 ± 10.66 mm and 11.83 ± 13.49 mm for first and the second mobile node respectively. A similar experiment was conducted for orthogonal signals explained in Section 8.3.1.2 with the length of the waveform same as that in the former experiment. Here the length of $\mathbf{S}_1$ was set to 4.5 ms and $\mathbf{Tx1}$ and $\mathbf{Tx2}$ were of length 9 ms each. The errors in range measurements were found to be 2.16 ± 23.54 mm and -4.80 ± 25.40

mm, respectively. Hence, both multiple access methods were found to provide high accuracy for tracking two mobile nodes. The orthogonal chirp signals provided a lower mean error, while the variance of the error values was higher than that of up- and down-chirp.

8.6.2 Performance of Doppler shift Compensation

Initially, we examine whether the Doppler shift has a dominating effect on tracking performance during walking or not and then find the effectiveness of our Doppler compensation technique. We find the instantaneous velocity at which the foot moves away from the anchor node plane when the treadmill is operated at 3 kph and theoretically find the maximum error that may affect the measurements. We selected one subject's optical motion tracker gait data to find the instantaneous velocity of one of the lower limbs. The component of instantaneous velocity along the direction of the line connecting the center of the four anchor nodes and the moving mobile node was estimated. The maximum and the minimum of the velocity of the foot was found to be 1.3 and -0.7 m/s. Using Equation (8.10), the maximum and minimum error that is introduced in the measurement with either up-chirp or down-chirp was found to be 182mm and -98mm respectively which is 31.38% and 16.9% of maximum displacement along y-direction which is 580mm. This error is not acceptable and we need proper Doppler compensation techniques for accurate measurements. To evaluate the effectiveness of the proposed Doppler shift compensation, we employed a sophisticated optical reference system to determine the walking trajectory with sub-mm precision. The distances between the mobile nodes and four anchor nodes when one subject walks at 3 kph were obtained from the proposed system with Doppler correction and without Doppler correction using either up-chirp or a down-chirp. The mean absolute error (MAE) was calculated to compare the accuracy in each case and is listed in Table 8.1. The results of ultrasonic ranging before and after Doppler shift compensation presented in Figure 8.9 and Table 8.1 not only show that Doppler shift was dominating during walking but also the effectiveness of the proposed Doppler shift compensation algorithm in such an environment.

FIGURE 8.9: The comparison of the range measurements from one of the lower limbs to a fixed anchor node extracted from the proposed ultrasonic system using up-chirp, down-chirp, a mean of up and down-chirp and motion capture system for a walking speed of 3 kph

TABLE 8.1: Comparison of MAE for range measurement with and without Doppler correction

Transmitter No.	Range to Anchor No.	MAE using up-chirp (mm)	MAE using down-chirp (mm)	MAE after Doppler correction (mm)
1	1	103.72	99.03	9.45
	2	105.45	100.31	10.85
	3	94.95	85.88	11.92
	4	93.99	84.34	12.16
2	1	269.90	109.16	10.88
	2	270.88	116.09	10.95
	3	241.58	97.61	13.13
	4	241.93	95.78	16.43

8.6.3 Performance of Gait Tracking with Proposed Method

We implemented the multiple access method with up- and down-chirp signals along with the Doppler compensation explained in Section 8.3.2 in a low multi-path environment. RMSE between the 3D trajectories obtained from the proposed ultrasonic system and the reference camera-based system was used as a metric to benchmark the system performance. RMSE for each foot for five subjects is shown in the Table 8.2. First few samples before the subject starts walking were removed while calculating RMSE and correlation coefficient. The comparison of the 3D coordinates extracted from the proposed and reference systems are as shown in

FIGURE 8.10: The comparison of the 3D coordinates of one marker attached to one of the lower limbs extracted from the proposed ultrasonic system and motion capture system for a walking speed of 3 kph

Figure 8.10. The average values of RMSE along x,y, and z directions were found to be 16.75, 14.68, and 20.20mm, respectively. The results show that the system can provide high accuracy tracking along with good multiple access performance. PCC between the trajectories were calculated in the Y and Z directions. The mean PCC values were found to be 0.995 and 0.996 along y (horizontal) direction and 0.899 and 0.9326 along z (vertical) direction respectively for left and right foot.

8.6.3.1 Extraction of Spatial and Temporal Parameters

The step length, stance time, swing time, and maximum foot clearance were extracted from the 3D trajectories as explained in Chapter 3 [30]. The mean and standard deviation of the gait parameters are listed in Tables 8.3 and 8.4. The mean and standard deviation of the error between the parameters obtained from both systems at low and high walking speeds are listed in Tables 8.5 and 8.6. It can be observed from the tables that the errors in step length and stride time are comparable to the results for one mobile node in [204] and slightly higher at high walking speeds. The clinical validity of the system is mainly application specific.

TABLE 8.2: RMSE between the proposed and the reference system

Subject	Axis	1 kph		2 kph		3 kph	
		Left	Right	Left	Right	Left	Right
1	X	11.77	13.42	10.66	12.28	14.73	18.77
	Y	9.02	12.92	12.56	11.30	16.07	17.59
	Z	13.84	17.81	14.72	11.87	21.37	19.17
2	X	8.17	25.50	12.83	7.99	15.63	8.60
	Y	11.97	18.26	13.41	11.57	20.93	14.24
	Z	14.21	26.67	18.47	14.06	25.56	12.73
3	X	19.84	18.75	22.62	11.51	21.84	14.81
	Y	9.22	10.08	15.66	11.49	17.62	13.29
	Z	21.94	24.27	25.09	12.72	23.34	13.96
4	X	16.04	22.23	22.51	19.56	25.61	23.83
	Y	11.55	14.40	16.29	13.65	21.30	15.93
	Z	17.67	23.87	29.99	20.61	28.39	22.16
5	X	19.45	18.62	18.34	19	18.72	9.04
	Y	16.38	16.42	15.24	18.50	17.15	16.42
	Z	21.97	26.65	21.55	22	23.40	16.02

From Section 3.7 in Chapter 3, the maximum gait deviation in the step length for stroke subjects was found to be **15%**. From Tables 8.5 and 8.6, maximum error the proposed system introduces in the measurements were found to be **6.26%**. Hence, the system can considerably quantify the gait deviations in step length for stroke subjects. More study needs to be conducted with abnormal gait patterns to know the required accuracy for different applications. A Wilcoxon rank sum test was conducted to test the null hypothesis that the gait parameters extracted from both systems after removing the mean value of linear trend (bias) follow a distribution with equal medians after concatenating the gait parameters obtained from all trials from all the subjects. The test failed to reject the null hypothesis with p greater than 0.05 at 95% confidence level.

The Bland-Altman plots [185] depicting the difference between the gait parameters extracted from both systems for one subject are shown in Figure 8.11. The upper and lower limits of agreement were mean difference $\pm 2 \times$ standard deviation (SD) of the difference. The plots show an agreement between both systems with limits of agreement [62.1 -64.64] mm, [70.01 -15.8] mm, [52.17 -68.84] ms, and [34.01 -52.52] ms for step length of left leg, step length of right leg, swing time of left leg

TABLE 8.3: Comparison of mean and standard deviation (STD) of gait parameters estimated from the ultrasonic system and the reference camera system for the left lower limb.

	Subject		1	2	3	4	5
Step Length (mm)	Camera	Mean	361.88	523.45	521.85	455.6	494.05
		STD	13.67	29.33	13.32	15.38	27.17
	Ultrasound	Mean	334.63	491.23	505.44	441.95	487.40
		STD	27.17	40.18	32.65	39.38	35.34
	RMSE		35.29	39.75	32.14	36.86	28.77
Stance Time (ms)	Camera	Mean	526.90	699.05	742.71	679.92	754.58
		STD	29.67	33.73	42.54	36.76	33.49
	Ultrasound	Mean	537.42	683.14	736.66	660.04	744.58
		STD	33.00	38.69	50.06	55.93	39.83
	RMSE		23.41	35.49	27.29	42.73	35.79
Swing Time (ms)	Camera	Mean	372.07	446.40	456.66	454.54	502.71
		STD	15.06	18.54	20.95	11.71	13.40
	Ultrasound	Mean	361.11	463.07	461.87	474.81	511.46
		STD	23.64	31.15	32.07	38.06	28.85
	RMSE		24.41	33.99	26.05	40.65	28.20
Max. Foot Clearance (mm)	Camera	Mean	125.96	157.37	128.56	141.39	180.67
		STD	6.56	12.52	6.73	2.47	3.02
	Ultrasound	Mean	119.08	186.66	161.44	139.57	198.73
		STD	15.59	42.32	30.69	31.55	31.26
	RMSE		16.78	51.39	45.58	30.97	35.47

and swing time of right leg respectively. The least count for the representation of temporal parameters in the plots was 8 ms as the sampling rate of the reference system was 120 Hz, which was found to be about 0.6% of the average stride time and thus the errors due to least count can be neglected.

TABLE 8.4: Comparison of mean and standard deviation (STD) of gait parameters estimated from the ultrasonic system and the reference camera system for the right lower limb.

	Subject		1	2	3	4	5
Step Length (mm)	Camera	Mean	366.61	508.53	515.9	445.51	488.36
		STD	13.92	33.07	16.35	15.24	34.99
	Ultrasound	Mean	346.68	484.34	488.79	433.24	478.06
		STD	23.47	31.55	24.12	32.05	37.22
	RMSE		27.29	26.36	34.40	30.44	23.39
Stance Time (ms)	Camera	Mean	532.18	706.66	739.63	665.72	746.46
		STD	27.94	35.38	40.47	34.39	23.86
	Ultrasound	Mean	537.35	717.03	730.48	653.22	731.46
		STD	33.27	39.29	48.65	37.58	23.30
	RMSE		24.37	17.03	24.45	24.30	18.82
Swing Time (ms)	Camera	Mean	367.81	438.70	459.75	470.64	507.29
		STD	14.43	15.61	24.57	19.56	10.71
	Ultrasound	Mean	362.64	428.70	469.51	482.01	522.08
		STD	24.45	16.91	30.93	24.51	16.73
	RMSE		20.82	17.83	23.71	19.78	19.68
Max. Foot Clearance (mm)	Camera	Mean	127.07	144.97	112.47	153.95	181.05
		STD	8.55	12.07	4.23	3.21	4.16
	Ultrasound	Mean	123.74	142.55	117.69	166.68	187.10
		STD	23.97	20.02	18.38	37.25	20.24
	RMSE		23.88	15.50	17.93	39.12	20.07

8.6.4 Bilateral Gait Deviation Measure

In order to find the phase difference between the lower limbs, the unbiased correlation outputs, $\mathbf{A}_c(t)$ and $\mathbf{C}_c(t)$ for one subject walking at 3 kph from the proposed ultrasonic system are as shown in the Figure 8.12. Table 8.7 shows the bilateral gait deviation measure and the phase difference estimated between the limbs along the horizontal and the vertical directions obtained from the proposed system and

TABLE 8.5: Mean and Standard deviation (SD) of error between the gait parameters estimated from the proposed and motion capture system at a walking speed of 1 kph. E[S] and E[ST] represents the error in step length and stride time respectively

Subject	foot	E[S] (mm)		E[ST] (ms)	
		mean	SD	mean	SD
1	left	-9.80 (3.70%)	14.11	-0.18 (0.01%)	19.8
	right	-16.02 (5.84%)	13.85	0.18 (0.02%)	15.2
2	left	-8.1 (1.99%)	9.25	0 (0.00%)	17.7
	right	6.26 (1.53%)	27.13	-0.95 (0.06%)	40.1
3	left	-0.15 (0.12%)	24.74	-2.2 (0.14%)	44.5
	right	-17.07 (4.13%)	15.88	0.81 (0.05%)	37.2
4	left	3.39 (0.91%)	15.05	0.47 (0.03%)	32.4
	right	-3.22 (0.87%)	18.62	0.00 (0.00%)	20.2
5	left	-1.27 (0.30%)	20.34	-4.2 (0.24%)	46.6
	right	-13.18 (3.01%)	14.69	0.03 (0.02%)	26.5

TABLE 8.6: Mean and Standard deviation(SD) of error between the gait parameters estimated from the proposed and motion capture system at a walking speed of 3 kph. E[S] and E[ST] represents the error in step length and stride time respectively

Subject	foot	E[S] (mm)		E[ST] (ms)	
		mean	SD	mean	SD
1	left	-13.12 (3.62%)	30.12	1 (0.11%)	26.5
	right	-19.92 (5.43%)	18.81	0.00 (0.00%)	17.6
2	left	-32.79 (6.26%)	23.21	-0.07 (0.06%)	24.8
	right	-24.19 (4.75%)	10.58	-0.03 (0.03%)	15.6
3	left	1.22(0.23%)	31.71	0.08 (0.07%)	40.5
	right	-27.10 (5.25%)	21.45	-0.06 (0.05%)	23.2
4	left	-26.95 (5.91%)	32.14	-0.07 (0.06%)	43.4
	right	-24.99 (5.6%)	28.30	-0.09 (0.08%)	41.3
5	left	-6.65 (1.35%)	28.34	1.20 (0.09%)	37.7
	right	-10.30 (2.11%)	21.27	0.02 (0.01%)	15.3

FIGURE 8.11: Bland-Altman plots comparing step lengths of (a) left and (b) right lower limbs and swing times of (c) left and (d) right lower limbs calculated from the proposed system with the motion capture system at 3 kph walking speed for one subject. The upper and lower limits are marked as mean difference $\pm 2 \times$ standard deviation (SD)

FIGURE 8.12: The unbiased auto-correlation of y-coordinate of reference limb ($Ac(t)$) and the cross-correlation of y-coordinates of both lower limbs ($Cc(t)$)

the optical motion capture system. Here, we also considered an abnormal gait pattern with simulated leg length discrepancy to know the variations in the proposed gait deviation measure. To simulate the leg length discrepancy, we increased the thickness of the sole of the right lower limb by 50mm. The fifth subject was instructed to repeat the experiment to study the tracking performance for abnormal gait patterns with an extra sole thickness of 50 mm for the right lower limb. It can be observed from Table 8.7 that the phases estimated from the ultrasonic system as well as the camera system lie closer to 180° including the subject with simulated leg length discrepancy. However, the introduction of 50mm leg length discrepancy

TABLE 8.7: Mean bilateral gait deviation (BGD) and the mean phase difference between the left and right lower limbs for five healthy subjects and one abnormal subject (ABN)

Sub.	Speed (Kph)	$BGD_y(\%)$		Phase (Deg.)	
		US	Cam	US	Cam
1	1	5.08	6.12	176.02	179
	2	5.45	5.88	178.84	180
	3	5.84	6.01	175.68	178.92
2	1	4.04	5.42	187.17	184.55
	2	5.91	5.16	176.68	177.85
	3	4.65	5.14	180.2	180.91
3	1	4.58	6.78	179.89	180.44
	2	3.73	4.87	181.65	181.44
	3	4.58	5.60	180.22	179.65
4	1	4.9	5.85	187.05	183.64
	2	4.03	5.00	181.65	181.21
	3	5.1	5.47	179.45	179.99
5	1	4.22	4.96	183.35	182.73
	2	4.6	4.74	180.65	180.76
	3	4.26	3.61	178.03	178.69
ABN	1	4.28	5.97	184.85	182.69
	2	6.28	5.83	179.76	180.84
	3	7.66	7.64	181.21	181.21

slightly increased the bilateral gait deviation measure along y (BGD_y) direction at a walking speed of 3 kph. Figure 8.13 shows the y and z coordinates after removing the phase difference between the left and the right limbs. It should be noted that the proposed bilateral gait deviation measure takes inter-gait cycle variability into account as more than one gait cycle is considered during the calculation of the phase shift between the limbs. Figure 8.14 shows the 95% confidence interval of BGD_y values estimated for each gait cycle at walking speed of 3 kph assuming t-distribution. The number of samples for each subject was equal to the number of gait cycles which was greater than 30 for all subjects. The trend of both plots in Figure 8.14 shows a positive correlation with coefficient 0.896. The null hypothesis that BGD_y from both systems comes from the same distribution cannot be rejected with p greater than 0.05 in all cases. Table 8.8 compares the mean and standard deviation of step widths estimated from both systems. In summary,

FIGURE 8.13: The 3D trajectories of y and z coordinates of right and left lower limbs after removing the phase difference.

TABLE 8.8: Mean and Standard Deviation (STD) of the step width estimated from both systems.

Subject	Speed (Kph)	Ultrasound (mm)		Camera (mm)	
		Mean	STD	Mean	STD
1	1	125.24	27.04	117.34	12.01
	2	131.27	18.63	121	12.68
	3	120.33	32.42	115.64	14.47
2	1	150.92	37.05	146.26	10.14
	2	153.68	21.8	152.22	8.63
	3	153.4	18.38	152.94	10.72
3	1	106.37	33.47	95.82	13.69
	2	107.97	43.89	102.15	24.13
	3	96.48	42.18	103.33	14.93
4	1	136.19	33.72	136.39	12.5
	2	132.19	48.21	141	18.74
	3	122.72	45.97	137.66	20.2
5	1	147.48	54.8	146.04	15.44
	2	132.17	47.69	128.4	12.09
	3	164.33	35.7	156.15	11.72
ABN	1	144.28	30.5	148.1	9.49
	2	143.78	30.39	142.54	13
	3	133.67	68.65	142.7	18.66

FIGURE 8.14: Plot showing **95%** confidence interval of the gait deviation measure extracted from ultrasonic and camera systems.

we were able to extract the gait parameters and gait deviation measures from the proposed ultrasonic gait analysis system accurately.

8.7 Conclusion

In this chapter, the design of a gait analysis system to track both lower limbs simultaneously during an indoor treadmill walk was proposed with a Doppler-tolerant multiple access ultrasonic localization system. We utilized various chirp signals as pulse compression with chirp signals can provide high ranging accuracy. The accuracy of the gait trajectories obtained from the proposed system was benchmarked with an optical motion capture system for three different walking speeds and five subjects. The system provided high accuracy for tracking along all three coordinate axes for both mobile nodes at 1, 2, and 3 kph. The average values of RMSE along x, y, and z directions were found to be 16.75, 14.68, and 20.20mm, respectively. A high correlation between the trajectories was observed along the horizontal and vertical directions. The errors in the spatial and temporal parameters estimated from the proposed system compared with the motion capture system were also quantified.

The main disadvantages of the proposed gait analysis system are the errors caused due to the non-line of sight and the limited directivity of the ultrasonic transducers. Loose clothes of the subject which may obstruct the LOS can also lead to errors in

the measurement. In this work, we did not try to optimize the size of the wearable sensors and power consumption. These issues can be addressed in the future.

Chapter 9

Conclusion and Future Work

9.1 Conclusion

In this thesis, the design and development of a human motion tracking system based on wearable ultrasonic sensor nodes are presented. Ultrasonic waves travel at a slower velocity compared to electromagnetic waves and thus relaxes the strict constraints on clock synchronization for ToF ranging compared to other electromagnetic waves. We used narrowband ultrasonic sensors in our wearable gait analysis systems as they are cheaper and consumes less power and voltage compared to broadband ultrasonic sensors. We proposed methods to increase tracking performance, enable multiple access, provide multi-path compensation, and Doppler correction in narrowband ultrasonic sensor networks with correlation receivers. We tested the methods in a wireless wearable gait analysis system, and benchmarked the system with an optical motion capture system.

- Initially, a gait analysis system with wearable wireless UWB sensors was designed using double-sided two-way ranging and the performance was compared to similar ultrasonic sensors. One wearable mobile node on the lower limb and four fixed anchor nodes were used. UKF was used to estimate 3D trajectories from the range measurements. For static measurements, the standard deviation for ultrasonic sensors was found to be 11.22mm compared to 25.12 with UWB sensors. The net-RMSE for the gait analysis system for UWB was found to be 96.38, 90.33, and 97.63 mm at 1, 2, and 3 kph compared to 41.19, 41.52, and 42.99 mm for narrowband monotonic ultrasonic

signals. It was found that the ultrasonic systems provided better accuracy in a wireless environment, thus we studied the methods for ToA ranging in narrowband ultrasonic sensors using chirp signals.

- Linear frequency modulated narrowband ultrasonic chirp signals were selected for ranging with one mobile node and four fixed anchor nodes, and two different Doppler-correction methods are tested: (1) Pilot-carrier based method and (2) Range-Doppler coupling neutralization method. Both methods performed better compared to traditional methods like a bank of correlation receivers. Range-Doppler coupling neutralization method gave the best results for Doppler correction maintaining the same data update rate. From simulation experiments, pilot carrier method gave 12.52 mm MAE and range-Doppler coupling neutralization method gave 0.68 mm MAE for ranging between one transmitter and four anchor nodes. A pendulum experiment was conducted to compare the performances of Doppler correction methods. Range-Doppler coupling neutralization method gave best results with net-RMSE 14.19 mm followed by Pilot-carrier method with net-RMSE 27.43 mm. A bank of correlation receivers at the receiver side didn't give satisfactory performance for Doppler correction. We also proposed a method to compensate for the ranging errors due to close multi-path components for one mobile node. For static measurements, the standard deviation of the measurements decreased about five times with the proposed method compared to the conventional peak detection correlation receivers. A gait analysis system with one wearable node was designed with the proposed multi-path and Doppler correction methods. The 3D tracking accuracy was compared to the optical motion capture system and the net-RMSE was found to be 19.86, 21.81, and 25.16 mm respectively for 1, 2, and 3 kph walking speeds respectively. The mean value of net-RMSE improved from 28.70 to 22.28 mm with the proposed close multi-path compensation method.
- Going from one mobile node to multiple mobile nodes, we tested the performance of spatial division multiple access in tracking two mobile nodes using single-tone ultrasonic pulses. A gait analysis system was designed to test the performance of this method. The mean values of the net-RMSE with reference to the motion capture system obtained for five healthy subjects while tracking both feet simultaneously in millimeters were found to be 27.67, 32.01 and 35.63 for a walking speed of 1, 2 and 3 kph. The data update rate of

the system was not affected going from one to two mobile nodes as spatial division channel multiple access was used. Spatial and temporal parameters such as step length, swing time, stride time, step width, etc. were extracted from the 3D trajectories. A method to track lower limb joint flexion and extension angles using only two wearable mobile nodes was proposed and a pilot study was conducted to test the error tolerance of the method with motion capture database of ten subjects. We use inverse kinematics and damped least-squares in the method. The MAE for hip and knee joint angle was found to be within 5° for medium and low noise levels except for knee angle at a medium noise level which is slightly higher at 5.22° . This shows that the hip and knee joint angles can be tracked using only two wearable nodes during gait with moderate error tolerance; however, the method needs to be tested with wearable ranging sensors and abnormal gait patterns in the future.

- SDMA requires a large number of fixed anchor nodes with known positions and enough spatial separation between simultaneously transmitting mobile nodes. Thus, methods for channel multiple access for simultaneous sensor identification and ranging without affecting the data update rate of the system were studied in detail. We tested chirp diversity multiple access and simultaneous Doppler correction in narrowband ultrasonic sensors using a pendulum experiment with four ultrasonic transmitters simultaneously sending coded chirp signals. Two kinds of range-Doppler coupling neutralization methods were implemented with orthogonal coded chirp signals: (1) Mean-measurement method and (2) Doppler velocity compensation method. The simulation results with four transmitters gave a mean value of the standard deviation as 26.09 and 13.8 mm respectively for Mean-measurement and Doppler velocity compensation method at 0 dB SNR. A Pendulum experiment was also conducted to find the ranging performance when four nodes transmit simultaneously. The mean value of standard deviation of error was found to be 4mm for both methods at lower moving velocities. Range-Doppler coupling neutralization method for simultaneous multiple access and Doppler correction was implemented in a gait analysis system using two mobile nodes attached as markers on the lower limbs for motion tracking. The system gave good performance with net-RMSE between the trajectories 30.30, 28.55, and

32.01 mm respectively for walking speed of 1, 2, and 3 kph. Spatial and temporal parameters were extracted from the proposed system and compared to that of the motion capture system. A new bilateral deviation measure was also derived to quantify the bilateral gait symmetry in terms of 3D coordinates. The proposed bilateral gait deviation measure extracted from the ultrasonic system and optical motion capture system gave a positive trend with a correlation coefficient of 0.896 when experiments were conducted with five different healthy subjects and one subject with a 50 mm simulated leg length discrepancy.

9.2 Future Works

Plans for future works are briefly explained below:

1. **Grouping Helen Hayes marker set so that chirp division multiple access and spatial multiple access can be combined to get a complete gait analysis system:** We modified the Helen Hayes marker set for complete 3D gait analysis and grouped markers into groups of three or four, and each group can be tracked by a separate receiver plane with four anchor nodes. A small bandwidth of 4-10 kHz can be utilized for multiple access and Doppler correction with cheap piezoelectric transducers. The grouping was done so that all markers are visible by the corresponding receiver boards. The spatial division between the receiver planes can help in channel multiple access; however, each marker assigned for the same receiver plane can transmit at the same time using the chirp diversity multiple access and Doppler correction proposed in our work. The grouping of markers is as shown in Figure 9.1.
2. **Use of OpenSim to predict the muscle moments from kinematic data collected:** OpenSim is an open-source platform for modeling, simulating, and evaluating the neuromusculoskeletal system. To simulate movements in OpenSim such as human gait, motion-capture protocols that carefully describe subjects' joint axes, trunk motions, and limb motions are required. Conventional protocols for clinical motion analysis using different kinds of sensors were not designed with the intent of building simulation models, and

FIGURE 9.1: Representation of full body 3D gait analysis using a combination of spatial and chirp division multiple access.

they could be improved by using ultrasonic sensors [205]. The limitations of motion capture data and its solutions using ultrasonic systems need to be studied in detail. Ultrasonic systems can be scaled for accommodating more number of mobile nodes which provide tracking accuracy comparable to the camera-based motion capture system. Full body kinematic data collected using the ultrasonic system along with ground reaction forces can provide required simulation inputs for typical Opensim models.

3. **Use of redundant anchor nodes to increase the coverage of the motion tracking system:** The use of multiple sensors to increase the capture volume or use of cone-reflector to make the ultrasonic signals omnidirectional [206] are also potential research opportunities in the future. Abnormal gait patterns of patients can be studied with the developed gait analysis system. Subjects with various neurological disorders can be recruited to find how this system can be effectively used for daily clinical gait analysis in the rehabilitation process. To collect the data from patients in clinics, where the existing method of analysis makes the patient walk on level ground, we can increase the number of anchor nodes carefully considering the coverage of ultrasonic waves to increase the tracking volume of the system so that the use

of treadmill can be avoided. The RSSI can be used as a parameter to select four anchors with best signal strength which can be used to track a particular mobile node. The size, weight and power consumption of the wireless mobile nodes also need to be taken care of in the future work. The sensors can be designed in the form of wearable bands to the upper and lower limbs. Sensors with higher bandwidth and flat frequency response provide higher resolution and better signal power at the receiver for chirp signals. The development of custom-made ultrasonic receivers incorporating MEMS technology makes the system robust and provides options for future developments.

4. **Optimizing number of mobile nodes in the proposed chirp diversity multiple access localization method for simultaneous detection, error correction, and ranging:** Finding the optimum number of mobile nodes that can be supported in the active mobile node localization system using the available bandwidth of the sensors and error correction codes lies in the scope of future research. Let us assume that C number of linearly increasing chirp-lets can be obtained from the available bandwidth of B Hz. The number of active mobile nodes be N and the time for one chirp-let be T_c . Some error correction schemes can be used for misidentification of transmitters. If we add P number of bits for error detection or error correction for coded chirp signals to communicate their identity, we need to send $\log_2 N + P$ number of bits in a single ranging cycle with up-chirp signals. For Doppler correction, we need to send the corresponding down-chirp signal in the next ranging cycle. Let the time difference between consecutive transmissions be T_s , then the total time for the transmission of up-chirp signals will be $(\frac{\log_2 N + P}{\log_2 C}) \times T_c + T_s$. Total time for ranging cycle with up and down-chirp signals can be given by

$$T = 2 \times \left(\left(\frac{\log_2 N + P}{\log_2 C} \right) \times T_c + T_s \right) \quad (9.1)$$

Hence, the data update rate can be given by:

$$R_u = \frac{1}{T} \quad (9.2)$$

In the future, custom-designed ultrasonic transducers with improved bandwidth can accommodate a large number of mobile nodes with a higher number

of chirp-lets ($\mathbf{C}$) maintaining the same data update rate as per Equation (9.2). However, it should be noted that these equations give the maximum capacity of the coding scheme and orthogonality of different signals are not guaranteed. Some iterative algorithms such as the one used in Chapter 7 need to be implemented to select the optimum orthogonal codes.

List of Author's Awards, Patents, and Publications¹

Journal Articles

- **Karalikkadan Ashhar**, Mohammad Omar Khyam, Cheong Boon Soh, and Keng He Kong (2018). A Doppler-Tolerant Ultrasonic Multiple Access Localization System for Human Gait Analysis. *Sensors*, 18(8), 2447.
- **Karalikkadan Ashhar**, Mohammad Omar Khyam, and Cheong Boon Soh (2019). A Multi-Path Compensation Method for Ranging in Wearable Ultrasonic Sensor Networks for Human Gait Analysis. *Sensors*, 19(6), 1350.
- **Karalikkadan Ashhar**, Md Noor-A-Rahim, Mohammad Omar Khyam, and Cheong Boon Soh (2019). A Narrowband Ultrasonic Ranging Method for Multiple Moving Sensor Nodes. *IEEE Sensors Journal*, 19(15), pp.6289-6297.

Conference Proceedings

- **Karalikkadan Ashhar**, Cheong Boon Soh and Keng He Kong, "A Wearable Ultrasonic Sensor Network for Analysis of Bilateral Gait Symmetry," *39th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC'17)*, JeJu Island, S. Korea.

¹The superscript * indicates joint first authors

- **Karalikkadan Ashhar**, Cheong Boon Soh, and Keng He Kong (2018, October). Wireless Ultrawideband Sensor Network for Gait Analysis in Rehabilitation Clinics. *In 2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC) (pp. 1524-1529). IEEE.*

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