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BIOMECHANICAL MEASURES FROM USING SMART BODY-WEAR SENSORS FOR GAIT ANALYSIS

A thesis submitted by

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QUOTES

*Said the Prophet **Muhammad** peace be upon him and his family*
“The best person is the one who benefits all human beings”
Believe the Messenger of Allah

ABSTRACT

There has been remarkable growth in the use of smartphone applications as a means of describing human movement. Accelerometer sensors in smartphones can be used to detect human movements and define gait characteristics. Photogrammetry approaches are used to study human gait for a variety of purposes such as medical, forensic and sport performance. This is a shift from insole sensors which were widely used to study human movements in recent decades. Importantly, each of the mentioned techniques can provide sets of data leading to a better understanding of human gait. For example, data extracted from insole sensors can be related to force and pressure, accelerometers mainly provide spatial-temporal parameter data, and photogrammetry data can better describe joint location (kinematics) during walking.

However, there is a lack of research literature assessing the accuracy of such smartphone use. Thus, the main aim of this work was to provide evidence for the applicability of smartphones as an effective tool for collecting biomechanical data and assessing human gait during walking. The current research work aimed to fill this gap in the literature by using a set of objectives comparing smartphones with other techniques.

The first objective was to identify existing accelerometer measurement data obtained from smartphone devices and evaluate this data by comparing captured data with camera image-based photogrammetric data. The data were collected during walking trials. Smartphones were attached to the subject's knee joints, and cameras were placed around a 5m-walkway at specific positions. Ten subjects (with no prior injury, disability or illness) were recruited and asked to perform a two steps walking trial, with five repetitions. The results indicated that the linear location values for the whole stance phase are relatively similar and closer to that of a camera's 3D location in the x y planes (Z direction) (R= 0.935) which supports the hypothesis of our research that the smartphone can be utilised as tool for gait characteristics measurements.

The remaining research objectives were to develop a new methodology for smartphone sensor device analysis of spatiotemporal gait parameters, and to compare the spatiotemporal data between the smartphones and F-Scan insole sensors during walking. Data were collected from both the triaxial accelerometer embedded in the

Samsung S9 cameras and insole sensors. Two smartphones, one attached to each lower limb, were used in this experiment. Thirty subjects were asked to walk along a 10-m walkway at a laboratory setting at the Exercise and Sport Science Centre at the University of Southern Queensland (USQ). Data for the four parameters of step time, stride time, cadence and walking speed were collected during walking. The results pointed out close data readings from both devices. For example, the step time findings were (0.68±0.02 insole) and (0.69±0.03), and the stride time findings were (1.21±0.05 insole) and (1.21±0.05).

From the results of the four parameters, it was noticed that there is a high agreement between the smartphone and insole sensor when measuring gait parameters. Furthermore, these results demonstrated that the smartphone sensor can efficiently measure the spatiotemporal gait parameters of healthy adult participants. Thus, smartphone sensors can provide reliable data without the need for expensive devices. Finally, the proposed study will help experts work more efficiently and objectively, and at less expense when evaluating gait.

CERTIFICATION OF THESIS

This thesis is the work of **Mustafa Naser Mnati Al-lami** except where otherwise acknowledged. The work is original and has not previously been submitted for any other award, except where acknowledged.

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Student and supervisor's signatures of endorsement are held at the University.

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ABBREVIATIONS

AROM	Active range of motion
CA	Contact area
CRP	Close-range photogrammetry
EMG	Electromyography
ETS	Electromagnetic tracking system
FF	Force foot
FRS	Force Resistance Sensors
GEI	Gait Energy Image
GPS	Global positioning system
ICC	Interclass Correlation Coefficient
IMUs	Inertial Measurement Units
KG	kilogram
LRS	Laser range scanners
L	Left
MEMS	Micro electromechanical systems
MF	Midfoot
MR	Magnetoresistive sensor
NWS	Non wearable system
PP	Peak Pressure
R	Right
RFS	Reaction force sensors
TEM	Technical Error of Measurement
TFL	Truncated foot length
TO	Teos
TOF	Time-of-Flight
WS	Wearable system
WB	Weight bearing
2D	Two dimensions
3D	Three Dimensions

CHAPTER 1 INTRODUCTION

INTRODUCTION

This chapter provides a general overview of the research topic. It presents the research gap, objectives, questions, significance and the scope of the research. It also outlines the structure of the thesis.

1.1 Overview

The importance of measuring and analysing gait variability has drawn the attention of many researchers and experts from different fields. The concept of human gait analysis is being used by specialists in wide range of fields such as sports, medicine, allied health and security (Tan et al. 2015; Akhtaruzzaman et al. 2016).

As limbs move, they generate a specific locomotion that is defined as human gait. These movements include walking, running and jumping. The study of human gait is considered to be one of primary methods providing significant information to assist human health. Human locomotion is described in terms of gait parameters such as walking cadence, velocity, step/stride length and step/stride time. A person's walking pattern can be assessed by gait analysis to determine abnormalities as well as any significant variation in gait parameters and potential consequences of those abnormal patterns. According to Muheidat et al. (2017), there are strong links between human gait characteristics and different medical conditions as proved in clinical research. Also, research shows that changes in certain gait parameters may be predictive of future falls and adverse events in older adults such as a physical functional decline (Viccaro et al. 2011; Taylor et al. 2012). Moreover, the progression of diseases affecting mobility has been monitored using the analysis of gait (Samà et al. 2012). Winter (2009) stated that Human Movement's biomechanics is considered to be a discipline that illustrates, analyses and assesses human movement. Winter (2009) emphases that this scientific area has attracted the attention of specialists, experts, rehabilitation engineers, doctors, athletes and therapists.

As a result of human gait analysis's many applications, an assortment of technologies are being created and investigated to evaluate and assess it. Most of the systems can be categorized into wearable devices, walk-on devices, radar and motion systems, and vision based devices and techniques (Liu et al. 2011; Nessler et al. 2015; Iosa et al. 2016). Many factors affect system choice: cost, portability and active involvement by the user. Many systems are suitable for only the laboratory or clinic setting, e.g. GAITRite Electronic mat and the Vicon motion capture system (Peters et al. 2014; Mjøsund et al. 2017) .

A wearable device is an electronic device that can be attached to the body or embedded in a garment, and is able to record information about the user's body movements by analysing the signals produced by the device's transducers (Del Rosario et al. 2015). Wearable sensors have experienced a remarkable growth in application, such as in the security, medical and commercial fields. They provide accurate and reliable information about human movements and activities, so they can be very beneficial in human movement studies. With regular movements, wearable sensors can manage and evaluate chronic diseases such as obesity (Turner et al. 2015). Wearable sensors are also valuable tools for athletes; enhancing their personal health status because they can provide individualised feedback during training sessions, evaluate running and dynamic sway in the gait of athletes, etc. (Blank et al. 2014; Moran et al. 2015; Brodie et al. 2016).

The characteristics of wearable sensors (low power, small size and light weight) allow researchers to monitor movement and gait characteristics over long periods of time (Gong et al. 2015). In addition, they should not affect the performance of subjects as they can be attached or embedded into clothing or smartphones. Several sensors can be embedded in smartphones, such as accelerometers, gyroscopes and magnetometers. Obtaining accelerometer data from smartphones has become a very interesting subject in current studies, with successful application and good results (Manor et al. 2018; Nelms et al. 2020). Accelerometer sensors can be used to obtain data related to a user's gait without obstructing the user as he/she walks. Many recent gait studies have used smartphone sensors (Fernandez-Lopez et al. 2016): human movement (Bulbul et al. 2018) and sport (Kos et al. 2018).

In this research, a new technique will be applied to the study of human movement using smartphone sensor accelerometer data. Hence, the purpose of this research is to develop a low-cost, high quality and easily used approach by replacing the photogrammetry technique and insole sensors with a smartphone sensor. However, no such study has been done exactly same comparison before to obtain biomechanical measures and smart body-wear devices for gait.

1.2 Gap in the research

From a review of the literature (detailed in the second chapter), it can be seen that human movements and gait characteristics have been studied using various devices such as cameras, and pressure and force sensors. However, these devices have some disadvantages such as being costly, requiring space, being time consuming and requiring active involvement from the user. Recently, research scientists have become interested in developing new measures based on smartphone technology, but the existing literature has not reported any work that:

a) Suitability of smartphones compared to photogrammetry techniques
b) Suitability of smartphones compared to insole sensors.

These ideas to evaluate the smartphone can increase the validity of smartphone in gait analysis research.

Therefore, the research gaps in the field of human gait analysis are:

1) Evaluate smartphone accelerometer technology as a replacement for current photogrammetry techniques using imaging sensors.
2) Develop a set of human movement measures using advanced technologies.

1.3 Research Questions

There are a number of crucial questions for this research. These questions are:

1) To determine the existing measures suitable from body-wear devices for gait research:
    a) What are the types of smartphone sensors to be evaluated in this research and why?
    b) Why it is crucial in gait study to put the body-wear sensors in lower limb?
2) To evaluate the most suitable set of devices by comparing the data resulting from smartphone accelerometer sensors with camera images data.

3) To evaluate smartphone based biomechanical measurements for the study of gait characteristics using a cohort of 30 adults:
   a) What protocols should be used in this research?
   b) How will spatiotemporal gait data be analysed?
4) What are the benefits of using the proposed methodology in the field of gait analysis?
5) Are commercial accelerometer smartphone sensors suitable for determining gait human movements?
6) How to use the new statistical testing methods to analysis gait data of healthy groups.

1.4 Objectives

The main aim of this research is to study a new technique to evaluate smartphone-based biomechanical measures for gait characteristic analysis. To achieve this aim, four objectives were formalised:

1) To identify research gaps in the existing literature regarding the introduction of a new evaluation technique for smartphone sensor devices which can be achieved by:
   a) Determining existing accelerometer measurements obtained from smartphone devices
   b) Comparing captured data with camera image-based photogrammetric data.
2) To develop a new methodology for smartphone sensor device analysis of spatiotemporal gait parameters.
3) To determine the suitability of new gait parameters characteristics to identify and relationship between Smartphone and Insole sensors.
4) To evaluate the performance quality of the proposed methods using different statistical methods and comparing the results of the novel methodology with those of the most commonly used methods discussed in published works.

1.5 Limitations of the research

This research has three limitations that should be acknowledged. These are:

1) Synchronization of accelerometers with digital cameras (possible timing errors).
2) Use of commercial smartphone sensors which may not be the most accurate.

   For example accelerometer sensor characteristics are Vender:STC, version:1 , max range:78:453m/s^2 and Resolution:0.002 m/s^2
3) Walking at speed and running were not tested during this investigation because of the limited dimensions of using wiring system.

1.6 Significance of the research

Completing this research will bring a number of benefits to conducting human gait analysis. These benefits are:

1) Analysis of various aspects of gait, including turns, gait initiation and termination, or inter-cycle variability.
2) Demonstration that smartphone sensors, such as accelerometers, can provide accurate and efficient data compared to the photogrammetry technique in gait studying.
3) Development of a new technique to analyse the spatiotemporal parameters with less money, effort and time.

1.7 Structure of the thesis

This thesis consists of five chapters and each chapter provides important information on that study. The rest of the thesis is structured as follows:

- **Chapter 1** is the introductory chapter, explaining the background and definition of human gait, the research problems and aims, the research objectives, the significance of the research and the structure of the thesis.

- **Chapter 2** forms the literature review, presenting the importance of human gait analysis, non-wearable and wearable systems, close range photogrammetry and the smartphone platform.

- **Chapter 3** is divided into two parts and describes the instrumentation used to perform the study's experiments. The first part shows the measurement systems used to measure kinematics of the lower limb movements, the test protocol, camera calibration and photogrammetric data capture, data collection from the accelerometer's smartphone sensor, calculation, and statistics. This part compares and validates the use of the smartphone and camera. The second part describes the new evaluation methodology for spatial parameters. It shows the equipment, the plantar pressure measurement system, participants, protocol test, data collection and processing, and statistical analysis.

- **Chapter 4** presents the accelerometer test, photogrammetry test, insole sensors, kinematics and spatiotemporal parameter results while walking in different trials. It also presents the analysis techniques used to evaluate and validate the presented methods.

- **Chapter 5** presents the main discussions points of the research conducted, and the conclusion of the thesis.

- **Chapter 6** presents the conclusion of the thesis and the future work.

CHAPTER 2 LITERATURE REVIEW

This chapter provides both a background to human gait analysis and a literature review of its major elements, as well as citing some of its applications. It then focuses on gait analysis method by highlighting non wearable and wearable devices that are used to study gait and human movement and critically reviewing the advantages and disadvantages of both types of methods. The chapter also gives a brief of smartphone platforms and smartphone techniques and sensors.

2.1 Introduction

Currently, many research projects have addressed human gait analysis. The very beginning of the research on this type of analysis was in the 19^{th} century. The majority of such projects needed to study the variety of parameters that characterise gait, so they have focused on achieving quantitative objective measurements of these parameters to be applied in the various fields such as sports (Howell et al. 2017), and medicine (Schwenk et al. 2014). Two approaches are used to analyse gait parameters. The first one used is the semi-subjective method, which uses traditional scales. This can be done by patient walking and it is usually followed by a survey in which the patient is asked to provide a subjective evaluation of the quality of his/her gait. (Lord et al. 2012) This method gives subjective measurements, which may have a negative effect on the diagnosis, follow-up and treatment of the pathologies (Muro-de-la-Herran et al. 2014). In contrast, the second approach benefits from the remarkable growth in technology via devices and techniques such as camera floor sensors which allow an objective evaluation of different gait parameters, resulting in more efficient measurements and providing specialists with a large amount of reliable information on patients' gaits. Consequently, the error margin caused by subjective techniques can be reduced.

This chapter is divided into several sections and sub-sections based on the objectives and aims of this research. A general introduction is described in section 2.1. Section 2.2 is describing basic introduction into gait analysis protocol. Section 2.3 explains the importance of gait analysis in human movement studies. Section 2.4 explains the gait analysis methods and provide brief about the gait study systems such as non-wearable and wearable sensors. Section 2.5 is about close range photogrammetric technique, and 2.6 is about mobile platform.

2.2 Gait analysis

Human walking is a periodic movement of the body segments and includes repetitive motions (Winters et al., 2012). To describe this periodic movement, the human gait must be studied. Gait analysis is a method for evaluating the dynamic position and coordination during movement (Kavanagh and Menz, 2008). It can help in rehabilitation and therapy to note all the gait properties such as lower limb rotations and tilts, knee movement and foot placement (Bernardes & Oliveira 2017; Mirek et al. 2018).

To identify the functional importance of the different motions generated at the individual joints and segments, human walking patterns can be analysed by phases. There are eight different gait phases of the normal walking gait cycle: initial contact, loading response, midstance, terminal stance, pre-swing, initial swing, mid-swing, and terminal swing as shown in Figure 2.1 (Tao et al. 2012).

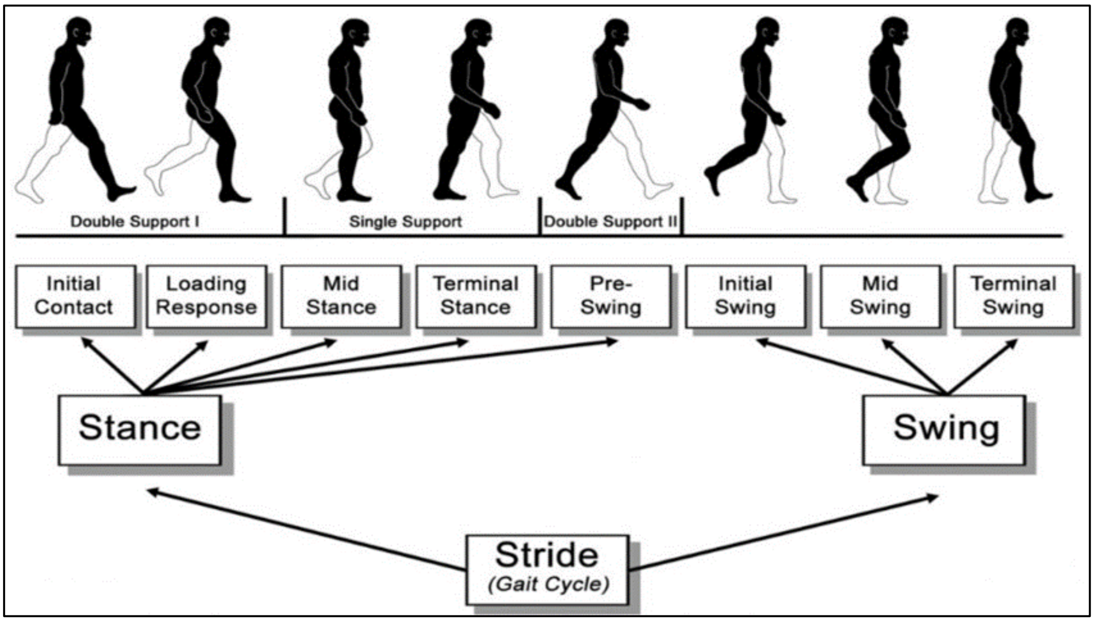


Figure 2.1: Gait phases in a normal gait cycle. Stance period and swing period

2.3 Human Gait Applications

2.3.1 Clinical purposes

Understanding human gait helps specialists to make more comprehensive diagnoses and provide more effective treatments for those who have ailments affecting their ability to walk normally. This awareness can thus be used to deliver better care to patients. According to (Anderson et al. 1997) , human gait analysis has been considered as a useful tool for physicians, therapists and clinicians for rehabilitation purposes in order to evaluate gait conditions of patients and then make appropriate treatment decisions.

Baker (2006) once treatment has commenced, human gait analysis can also be used to monitor patient progress and to predict subsequent treatment outcomes. Experts have employed such analysis to choose suitable orthoses for patients with abnormal walking conditions or to evaluate the efficiency of these devices (Brehm et al. 2011).

Other researchers have used human gait variables along with classification techniques to categorise patients into certain groups, and this is critical to such issues as the diagnosis of neuromuscular disorders (Yousefi & Hamilton-Wright 2014) or the prediction of falling behaviour (Begg & Kamruzzaman 2005).

2.3.2 Security purposes

Human gait analysis protocols were employed to identify and recognise people at a distance (Lee & Grimson 2002; Kale et al. 2003). One of the essential applications of recognition people using human gait analysis is for security purposes, where it can be used along with other techniques to detect criminals (Iwama et al. 2013). The researcher derived gait signature for the human walking pattern as each lower extremity has different pattern, thus they can be recognised by their walking style (Sun et al. 2016) .

Gait is a more valuable biometric than the others according to the fact that biometrics such as iris and face details are not easily recognised by surveillance applications at low resolution (Sulovská et al. 2013) .

2.3.3 Sports purposes

Athletes and sports professionals can benefit from gait analysis throughout monitoring performance parameters. That can lead to the detection of abnormalities and possibly increase athletic performance and reduce the risk of injury.

Parker et al. (2008) examined balance control during gait in concussed and uninjured athletes and non-athletes and they were assessed for their gait performance.

They found supposition that participation in high-impact sports has a measurable and possibly detrimental effect on balance control during gait.

Athletic performance

Watanabe & Hokari (2006) used gait analysis, particularly the kinematical analysis, to introduce a method that helps to make useful measurements to evaluate sports skills quantitatively.

Di Stasi et al. (2013) studied the differences between the gait characteristics of two groups of athletes, namely those who passed and those who did not pass the criteria of return-to-sport (RTS) six months after anterior cruciate ligament (ACL) reconstruction. They found that there are some differences between the two groups. In addition, they observed that those who did not pass the criteria of RTS had more abnormal and asymmetrical gait behaviours. These findings enable clinicians to have a testing criteria to recognise athletes with such abnormalities after ACL construction. They may also improve the sports medicine specialist's ability to identify athletes with a higher risk of secondary injury

2.3.4 Footwear design purposes

The footwear industry may also benefit from studies of human gait characteristics. According to Keenan et al. (2011), findings and results from such studies should be considered in future recommendations and designs of footwear. Bamberg et al. (2008) found that the footwear proved highly capable of detecting heel-strike and toe-off, as well as estimating foot orientation and position. As footwear plays an important role in correcting pathological gait and providing good foot support, the performance of some footwear has been studied regarding gait characteristics (Cheung & Zhang 2006). In addition, (Csapo et al. 2010) illustrated the importance of using suitable footwear in gaining good foot health.

It is well established that experts from any discipline need to follow the scientific approach when it comes to providing a solution for a particular problem or answering a specific question, and this particularly relates to footwear.

2.4 Gait Analysis Methods

Generally, human walking is a periodic movement of the body segments and includes repetitive motions(Winters et al. 2012). To describe this periodic movement, the human gait must be studied.

Gait analysis is a method for evaluating the dynamic position and coordination during movement (Kavanagh & Menz 2008). It can help therapists and other experts to note all the gait properties such as lower limb rotations and tilts, knee movement and foot placement. Two different methods to analyse human gait are non-wearable sensors and wearable sensors.

2.4.1 Non-wearable sensors

Non-wearable sensor (NWS) refer to sensors that are located on fixed places such as mats that the subject walks on (Muro-de-la-Herran et al. 2014) enabling the sensors to capture data regarding gait. Such systems might be categorised into two groups. The first group is based on image capture. In this group, one or more optic sensors are used to capture the subject's gait data and through digital image processing different parameters of the objective measurements can be taken (Courtney et al. 2001). Furthermore, there are another types of optic sensor such as laser range scanners (LRS) (Tanabe et al. 2017), infrared sensors and Time-of-Flight (ToF) cameras (Nakamura 2016). In contrast, the other system uses pressure sensors. The sensors here are located along the floor and the gait data will be gathered through pressure sensors and ground reaction force sensors (GRF).

Usually, the non-wearable sensors bring a high level of accuracy by using new gait spatiotemporal parameters (Panero et al. 2018) . However, because this method uses highly specialized equipment, it is expensive.

2.4.1.1 Image capturing

Image capturing is one of the processes used in gait studies. This process depends on using several digital or analogue cameras to obtain the gait information (Pratheepan et al. 2009). It also uses filters to obtain various characteristics of images. For example,

Figure 2.2: the snapshot of silhouette images of two walking people and their

Threshold filtering can convert images to black and white, and there are different ways to collect data to measure gait variables such as calculating the number of light or dark pixels or segmenting the background of the image. These methods have been widely studied in order to identify people by their walk (Chang et al. 2009) as shown in Figure 2.2. corresponding GEI's Gait Energy Image (Chang et al. 2009).

2.4.1.2 Pressure sensor

Pressure sensors are electronic devices that capture physical force contact to generate some sort of a response used to measure gait pressure and force when the subject walks on these mats as shown in Figure 2.3. It can provide very high performance and accurate measurements (Arafsha et al. 2018). Pressure sensors are divided into two types: force platforms and pressure measurement systems and both systems quantify the centre of pressure (Robertson et al. 2018). However, pressure measurement systems are useful for quantifying the pressure patterns under a foot over time but cannot quantify horizontal or shear components of the applied forces (Robertson et al. 2018). Pressure sensor have clinical applications such as the prevention of pressure ulcer (Liu et al. 2014). Liu et al. (2014) found the floor mat is available for the measurement of GRF and it cannot measure more than one stride.

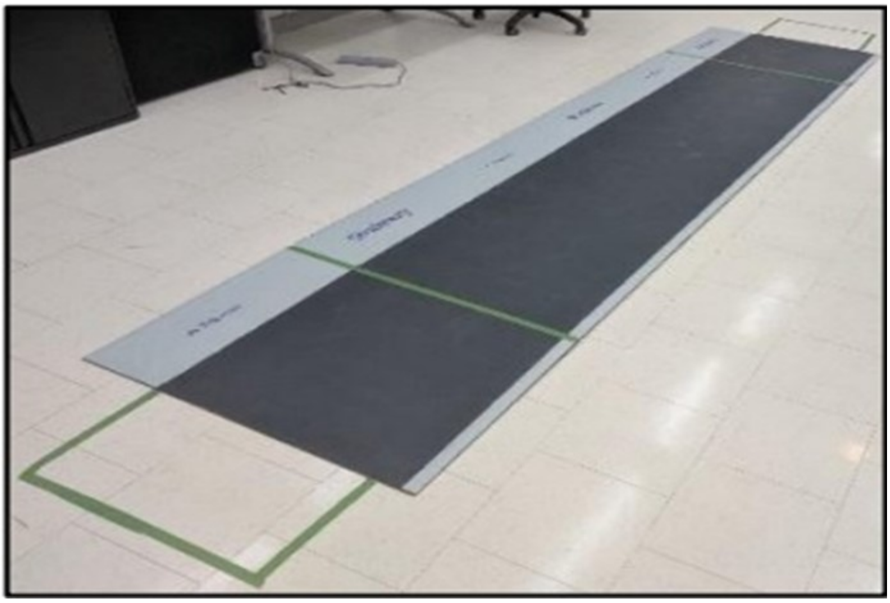


Figure 2.3: presser sensor showing marked start and stop boxes (Arafsha et al. 2018)

2.4.2 Advantages and disadvantages of Non-wearable sensors

The parameters of simultaneous analysis of multiple gait can be obtained by using a number of approaches. All systems are do not attach sensors to the body. Complex analysis systems are more precise and have more measurement capacity with better repeatability and reproducibility (Muro-de-la-Herran et al. 2014). However, they have less of an external factor interference because of a controlled environment. The process of undertaking measurements is controlled in real time by the specialist. At the same time, normal subject gait might be different because of the walking space restrictions required by the measurement system. Using an expensive equipment and tests are impossible to monitor a real life gait outdoor environment (Muro-de-la-Herran et al. 2014).

2.4.3 Wearable sensors

A wearable sensor (WS) is a category of devices that can be worn by a subject. A wearable sensor is an inexpensive, convenient, and efficient manner of providing useful information for multiple health-related applications (Tao et al. 2012).

These sensors are more flexible than NWSs because they can be used inside and outside the laboratory. In addition, they collect the subject's gait features during everyday activities. Such sensors may be worn on several parts of the body, such as feet, knees, thighs or waist. A variety of wearable sensors has been used to analyse gait characteristics, such as accelerometers, gyroscopes, flexible goniometers, electromagnetic tracking systems (ETSs), sensing fabrics and force sensors (Tong & Granat 1999; Bonato 2003) . Based on these sensors, either one or a collection of sensors may be used for various gait analysis applications depending on the required information. The basic principles and features of these motion sensors and systems are described below.

2.4.3.1 Accelerometer

This sensor is one of the most used sensors in human movements and gait analysis research. An accelerometer basically uses the fundamentals of Newton's Laws of Motion, which say that the acceleration of a body is proportional to the net force acting on the body (Muro-de-la-Herran et al. 2014). Based on this principle and using the physical changes in the displacement of the proof mass, with respect to the reference frame, the acceleration can be measured electrically. Two types of those sensors, piezoresistive sensors and capacitive accelerometers, are employed for measuring the motion status in the human gait (Bouten et al. 1997). By attaching these accelerometers to the feet or legs, the acceleration/velocity of the feet or legs in the gait to perform gait analysis (Zeng & Zhao 2011). Aaccelerometers are one of the most often sensors employed in gait analysis research. Accelerometer sensors are generally more user friendly and less invasive (Jarchi et al. 2018). They provided an extensive report of accelerometry-based gait analysis systems and applications, with additional emphasis on trunk accelerometer. Burgos et al. (2020) demonstrated the accuracy and reliability of in-ear accelerometer sensor to perform gait classification, between the activities walking and running. The data was collected from fourteen participants using a three-dimensional accelerometer sensor.

Another study demonstrated that a dual-accelerometer system previously validated in a laboratory setting also performs well in semi free-living conditions. Although these results are promising and progressive, further work is needed to expand the scope of this measurement system to detect other components of behaviour (e.g., activity intensity and sleep) that are related to health.(Narayanan et al. 2020).

Xiao et al. (2016) introduced statistical methods for predicting the types of human activity at sub-second resolution using triaxial accelerometer data. Their findings indicate that prediction of activity types for data collected during natural activities of daily living may actually be possible.

2.4.3.2 Gyroscope

A gyroscope is an angular velocity sensor. It measures inertial force, an apparent force proportional to the angular rate of rotation in a rotating reference frame. The angular rate can be measured by detecting the linear motion from the inertial effort and performing an integration of the gyroscopic signal. Gyroscopes based on other existing operating principles include electronic, microchip-packaged MEMS, solid-state ring lasers, fiber optic gyroscopes, and the extremely sensitive quantum gyroscope. A gyroscope can also be used for the measurement of the motion and posture of the human segment in gait analysis by measuring the angular rate (Altun & Barshan 2010; Ayrulu-Erdem & Barshan 2011). For example, to realize the reorganization of the various gait phases, the angular velocity and angle of feet or legs during the gait can be determined by attaching a gyroscope to human feet or legs. Most gait analysis studies combine a gyroscope and accelerometer to build a complete initial sensing system.

2.4.3.3 In-shoe systems

According to (Hsiao et al. 2002) in-shoe pressure sensor systems are one of the wearable sensors used to record the distribution of the pressure under the foot sole. This technology has emerged as a popular tool in many areas of clinical application and it possesses great potential as a useful tool in ergonomics research, such as in gait control and fall prevention. Various devices are available, which differ in size, sensor number, sensor type and therefore their response to loading and their accuracy. The strengths and weaknesses of each system in terms of validity and repeatability influence the appropriateness of each device for specific tasks in both clinical and research settings (Price et al. 2016). After fitting these sensors in suitably sized shoes, they are to be connected to a computer to capture the data through a software such as F-Scan research (Motawea et al. 2019). Figure 2.4 show one of this system.

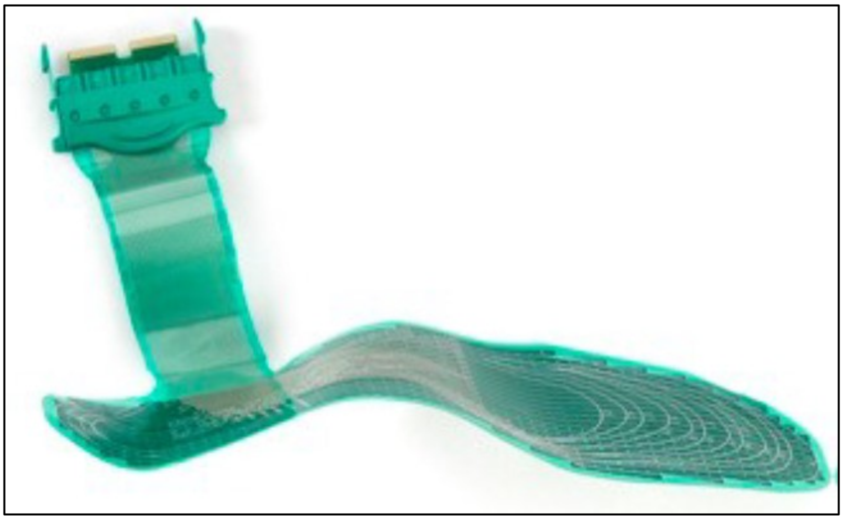


Figure 2.4: In-sole Sensor

2.4.3.4 Magnetoresistive (MR) sensors

Magnetoresistive (MR) sensors are linear magnetic field transducers based either on the intrinsic magnetoresistance of the ferromagnetic material (sensors based on the spontaneous resistance anisotropy in 3D ferromagnetic alloys, also called anisotropic magnetoresistance (AMR) sensors), or on ferromagnetic/non-magnetic heterostructures (giant magnetoresistance multilayers, spin valve and tunnelling magnetoresistance (TMR) devices)(Freitas et al. 2007).

2.4.3.5 GPS

The invention of the global positioning system (GPS) in the 1990s offered an optional strategy for the measurement of speed and position in the field, with the possibility of circumventing some of the limitations and minimising others (Townshend et al. 2008). GPS has been deemed a good way to study the movement of the human body , such as rotation and leg angles although it does not allow the researcher to conduct large-scale studies (Terrier & Schutz 2003). In addition, position and orientation errors tend to grow in an unrestrained way , and it is generally believed that the double integration of acceleration signals is not sufficiently accurate for the long-term monitoring of human motion (Foxlin 2002).

2.4.4 Advantages and disadvantages of wearable systems

The WS-based methods are conducted in laboratories or controlled conditions where data retrieval devices such as accelerometer, Gyroscope, Magnetoresistive (MR) sensors, In-shoe systems and GPS set to measure gait variables as the subject walks on a clearly defined walkway. The advantage of these systems are accurate analysis and monitoring of gait through daily activities or in the long term - Cheaper systems -Allows the possibility of deployment in any place, not needing controlled environments - Increasing availability of varied miniaturized sensors - Wireless systems enhance usability - In clinical gait analysis, promotes autonomy and active role of patients Disadvantage (Tao et al. 2012). WS systems make it possible to analyse data outside the laboratory and capture information about human gait during the person's everyday activities (Muro-de-la-Herran et al. 2014) .

Power consumption restrictions due to limited battery duration - Complex algorithms needed to estimate parameters from inertial sensors - Allows analysis of limited number of gait parameters - Susceptible to noise and interference of external factors not controlled by specialist (Muro-de-la-Herran et al. 2014).

2.5 Close range photogrammetry

In close-range photogrammetry (CRP), the camera is close to the subject and typically hand-held. It has become an accepted, powerful and readily available technique for engineers, scientists and others who wish to utilise images to make accurate 3D measurements of complex objects (Luhmann et al. 2014). This technique is used to track the 3-D position of a set of fiducial points which are constituted from either retroreflective (passive) or light-emitting (active) markers. The subsequent analysis of this information is analysed helping to estimate 3-D position data from digitized and noisy image data by using the geometrical properties of central projection from multi-camera observations.

It also has been used in the medical field (Chong et al. 2008; Chong 2011) as shown in Figure 2.5 and physiotherapeutic applications (Chong et al. 2008).

Figure 2.5: (Left) CMT imaging of the arm and hand; (Right) CMT imaging of the palm and fingers. Note the scale bar for quality control(Chong 2011).

In addition to the high precision and accuracy of the 3D multi-image photogrammetric technique such as (Chong, 2012; De Menezes et al., 2010), several advantages are provided. These advantages include its low cost when compared to other 3D measurement technologies (Chong, 2011; Chong, 2007), non-invasiveness (Ladeira et al., 2013), instantaneous data capture ability (Wong et al., 2008), ability for data post processing (Luhmann, 2010), and rapid data acquisition capability (Ladeira et al., 2013).

Galantucci et al. (2012) used system based on Digital Close-Range Photogrammetry with brand new equipment "stereoscopic digital cameras" to measure the facial soft tissue structures, useful for diagnostics and for the monitoring of therapies in medical and orthodontic applications. The scanner provides accuracy and reliability, is not invasive and very compact, simple and easy for physicians and doctors.

Another study developed a low-cost hardware/software system based on close range photogrammetry to track the movement of a person performing weightlifting (Colorado & Santos 2015). The goal is to reduce the costs to the trainers and athletes dedicated to this sport when it comes to analyse the performance of the sportsman and avoid injuries or accidents. Also, Al-Kharaz and Chong (2021) presented close-range photogrammetry technique to measure ankle kinematics during active range of motion in place. The finding of this study was that measurement of ankle kinematics during active range of motion AROM using the CRP technique was highly reliable and had perfect test-retest reliability (0.89).

2.5.1 Digital Video Camera

Recently, digital video cameras have been employed to capture human body movement and model the 3D surface of specific dynamic parts of the body such as the arm (D'Apuzzo 2003), the foot (Al-Baghdadi et al. 2011) as shown in Figure 2.6. In photogrammetry, different cameras located in different positions are used to measure or track the object (Luhmann 2014).In general, though, there are major limitations in utilising video camera systems to capture human movements. Firstly, such cameras have a limited number of image frames per second so they become useless to monitor and record a body's movement during a fast gait. Secondly, there can be long processing time depending on the number of cameras that require conversion of video clips to stereo images which are essential to derive a 3-D model.

Figure 2.6: (left) Video image of raised heel; (right) processed 3D surface model (Al-Baghdadi et al. 2011).

2.5.2 Data Acquisition

Data acquisition in photogrammetry is concerned with obtaining reliable information about the properties of surfaces (Whitehead & Hugenholtz 2014). This is accomplished without physical contact with the objects, the most obvious difference being with surveying.

The remotely received information can be grouped into four categories: geometric information, physical information, semantic information and temporal information (Ganapuram et al. 2009).

2.5.3 Data processing and analysis of photogrammetric methods

To generate 2D or 3D digital models of an object, digital image capturing and photogrammetric processing, including several well-defined stages, are used (Bistacchi et al. 2015). By using stereo image pairs, 3D data acquisition can be performed. Stereo photogrammetry is considered to be a fundamental approach for 3D mapping and object reconstruction using 2D images or based on a block of overlapped images (Tuovinen et al. 2013). Given a set of images depicting a number of 3D points from different viewpoints, bundle adjustment can be defined as the problem of simultaneously refining the 3D coordinates describing the scene geometry, the parameters of the relative motion, and the optical characteristics of the camera(s) employed to acquire the images, according to an optimality criterion involving the corresponding image projections of all points. Bundle adjustment minimises the total re-projection error with respect to all 3D point and camera parameters.

2.5.4 Video Camera Calibration

In photogrammetry, camera calibration is considered an important step in order to extract matric information from 2D images (Davison et al. 2007). This means the calibration can correct the camera distortion and determine the relation between the camera's natural units (pixels) and the real-world units (for example, millimetres or inches). Thus, the camera's calibration is significant step towards getting a highly accurate representation of the real world in the captured images. This technique can be accomplished by various methods such as dense reconstruction, object localisation and camera localisation. During the process of camera calibration, the interior orientation of the camera is determined. Foxlin et al. (2014) stated that all the metric characteristics of the camera needed for photogrammetric processes are described by interior orientation data. The interior orientation includes such elements as camera-calibrated focal length, the position of the perspective centre with respect to the fiducial marks, image quality measures and distances between fiducial marks to measure the coordinates.

2.6 Smartphone Platform

Smart mobile phones have become easy to obtain socially over the past ten years around the world. These smart devices provide a high technology platform for people as users and developers to explore mobile computing possibilities that present a promising ability for enhancing prevention, treatment and health issues (Pop-Eleches et al. 2011). This option has increased the demand for new mobile health (m-Health). Mobile developers have uses the benefits of this technology to maintain communication with patients and clinicians, as well as self-monitoring some health issues (Direito et al. 2014). In particular, Android mobile devices have been chosen by many m-health applications such as phones or tablets, as the target device to supply a more convenient user experience that has led to a rapidly increasing number of m-health pal Stores (Sinha et al. 2017). Also, Vos et al. (2016) used smartphone for supports personalized running experiences for less experienced runners. The ubiquitous nature of smartphone technology makes it an ideal platform through which to monitor human movement remotely without the cost of purchase and the inconvenience of use (Del Rosario et al. 2015) .

Tran and Phan (2016) designed and constructed a system to identify human actions using integrated sensors in smartphones and all Human activities recognition system is written on Windows and Android platforms and operate in real time.

Therefore, this research has selected the Android platform to represent mobile software platforms. Sony Z5 and Samsung S9 smart phone devices have been utilised for experiments.

2.6.1 Technical Specification

This research has used two smartphone. The first device is a Sony Z5 that has the following specifications: Weight: 154g, Dimensions: (146 x 72 x 7.3mm), OS: Android 6.0.1, Screen size: 5.2-inch, Resolution: (1080 x 1920) CPU: Snapdragon 810 RAM: 3GB Storage: 32GB Battery: 2900 mAh. The second device is a Samsung S9 which has the following specifications: height 5.81” (147.7 mm), width 2.7” (68.7 mm), depth 33” (8.5 mm), and weights (163 g), and screen size 5.8” (147.3 mm).

2.6.2 Smartphone Sensors

In most smartphones devices, there are a variety of sensors: Compass Magnetometer, Proximity sensor, Accelerometer, Ambient light sensor, and Gyroscope (Su et al. 2014). Recently, manufactured smartphone devices have adopted micro technologies to determine device orientation such as gyroscope accelerometers and micro electromechanical systems (MEMS) (Baldini et al. 2016). This research has focused solely on the efficiency of the accelerometer. Consequently, the review is focused on the one sensor of the Android application.

The accelerometer comprises up to three accelerometers, one for each axis-x, y, and z as illustrated in Figure 2.7 (Yousefian 2017). Each one calculates changes in the speed over time along a linear path. Combining all three accelerometers, the movement of the device in any direction and the current orientation of the device can be detected.

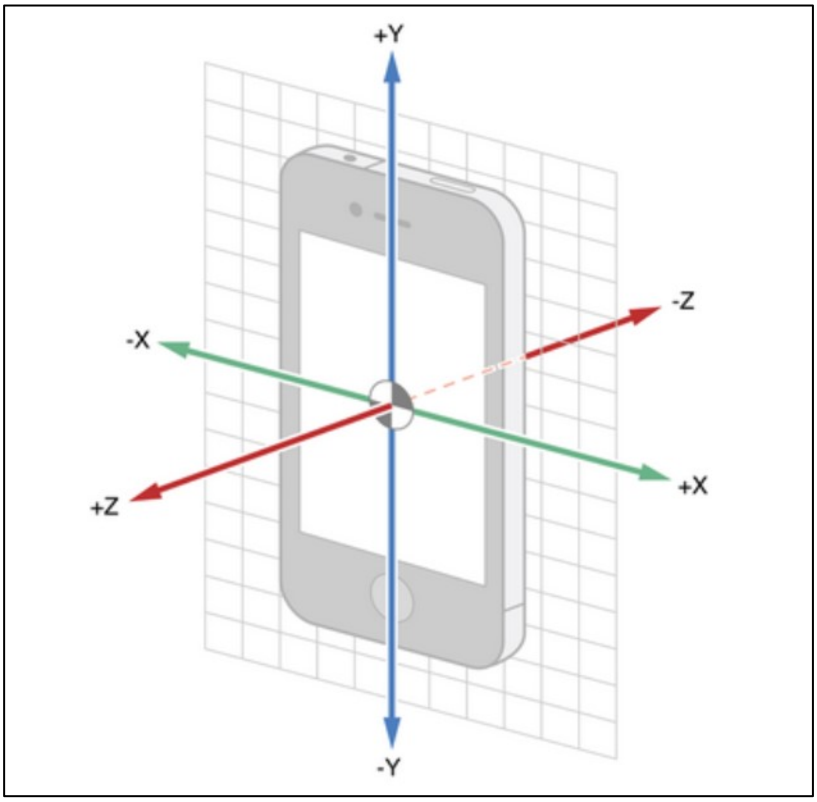


Figure 2.7: The accelerometer measures changes along the x, y, and z-axes.

The MEMS accelerometers in smartphone devices can provide accurate data of user's movements and may be helpful for gait analysis, evaluation, validation and monitoring (Tian & Chen 2016). Nishiguchi et al. (2012) evaluated the accuracy and validity of a smartphone accelerometer. The obtained outcomes by the smartphone showed statistically significant and reasonable agreement with the same parameter results obtained by the tri-axial accelerometer. Similarly, Chan et al. (2011) studied the abilities of the accelerometer in a smart mobile device for determination of gait events from walking over a flat surface. The outcomes confirm that it is possible to obtain features from the accelerometer of an iPhone such as step detection, stride time and cadence. Galán-Mercant et al. (2014) have further evaluated the reliability and accuracy of the accelerations with a smartphone in an Extended Timed Get Up and Go test. The results show that the internal sensor in the iPhone device is sufficiently accurate and reliable to validate and evaluate the kinematic patterns.

These studies have shown acceptable results which can enhance the smartphones' reliability for gait analysis. In addition, the built-in sensors of these smartphones devices can be as acceptable as IMUs. Thus, this research has explored the use of smartphones devices to analyse the walking measurements in real time for the estimation in gait analysis.

2.7 Summary

This chapter addresses the importance of studying human movement and gait characteristics. Also, this chapter demonstrates that many studies have used different methods and techniques to analyse human movements and gait characteristics the literature review shows that many studies have used photogrammetry techniques in science and engineering to make accurate 3D measurements of objects. Also, this research explained the gait analysis methods that are using in gait studies such as non-wearable devices and wearable devices. The advantages and disadvantages of both methods are explained in detail.

This section also found that by using smartphone sensors, gait research has continued to expand in the last decade. However, there is a lack of research investigating close-range photogrammetry with smartphones in terms of kinematics and need to develop a new technique to evaluate the spatiotemporal parameters via using accelerometers sensors measures. Therefore, the current work aims to fill this research gap by providing an understanding of the gait study methods, using new strategies and different ideas.

This aim has been achieved by applying a set of objectives to introduce a new technique for evaluating smartphone sensor devices in chapter 3. The first objective is to determine the suitability measures obtainable from Smartphone devices and comparing captured data with camera image-based photogrammetric data.

The second objective develops a new methodology for smartphone sensor devices to analyse spatiotemporal gait parameters. The third objective is to determine the suitability of new gait parameters characteristics to identify and the relationship between Smartphone and Insole sensors. Finally, this study evaluated and validated the performance's quality of the proposed method by using different statistical methods and comparing the results of the innovative methodology with those of the most used methods in published works.

CHAPTER 3 METHODOLOGY

3.1 Overview

This chapter describes how the objectives of the research were achieved. The main focus is the introduction of new protocols to collect accurate human gait data using cameras, smartphones and insole sensors.

This chapter has two parts. The first part (Section 3.2) begins by describing the methods applied to study the kinematics (distance and positions) of lower limbs during walking in the frontal plane. The structure of the measurements systems is illustrated in Section 3.2.1. The gait protocol used to perform camera calibration and capture photogrammetry data is explained in Sections 3.2.2 and 3.2.3. The smartphone calibration is then performed in Section 3.2.4, and data acquisition is illustrated in Section 3.2.5. The experimental measurements and analyses are addressed in Section 3.2.6. The methods reported in this part achieve the first objective. The second part of the chapter includes the methods applied to study the new evaluation methodology comparing smartphone accelerometer sensors and insole shoes sensors (Section 3.3.1), equipment (Section 3.3.2), participants' characteristics (Section 3.3.4), data collection (Section 3.3.5), and statistical analysis (Section 3.3.6).

This chapter also describes the materials and devices used during the data collecting procedures. The sampling strategy and conditions of participants are also introduced. The second part reports on the achievement of the second and third objectives

This research seeks to develop a new set of body wear-based (wearable) biomechanical measures for gait characteristics study. The system includes video cameras and smartphone accelerometer sensors. The set of body wear is verified by calculating data from the accelerometer sensors embedded in the smartphone and digital camera data. Then, data from the smartphone sensors and camera images is compared. Figure 3.1 shows the steps followed in the research methodology.

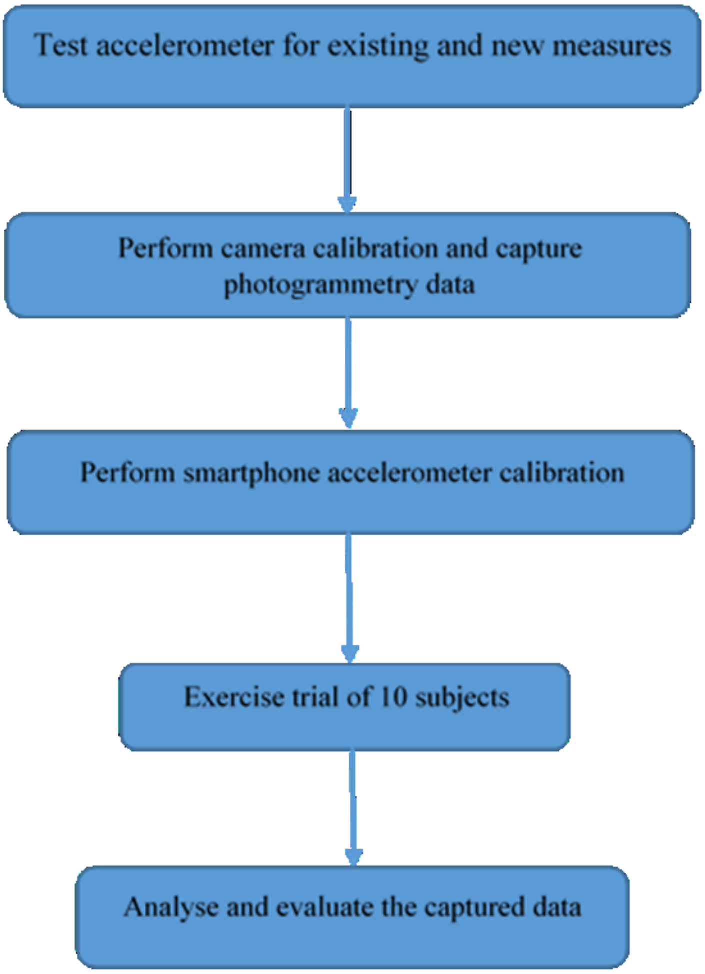


Figure 3.1: Research methodology outline (first part of methodology)

3.2 Kinematics (distance and positions)

3.2.1 Subjects and case description

To develop and evaluate the idea of the first part of this research, 10 male individuals aged between 30 and 45 years, weight 70-90 kg were recruited in the study as shown in Table 3.1. Participant weight is either in the normal range (Body Mass Index falls within a weight range that is not associated with an increased risk for weight-related diseases and health issues) or 20kg or more overweight. Participants had no previous injuries, trauma, illness or any related disorders.

Individual participants were fitted with the smartphone device around their right leg. Each subject was asked to walk two steps at their normal walking speed, and data was gathered. At the beginning of the test, the subject will turn on the program (inbox tool) manually and then start walking and record data for the test.

Table 3.1: Participants' characteristics

Participants	Height(cm)	Weight(kg)	Age
Subject 1	176	80	45
Subject 2	185	100	42
Subject 3	173	90	36
Subject 4	171	93	33
Subject 5	178	81	30
Subject 6	177	82	30
Subject 7	176	71	34
Subject 8	174	81	35
Subject 9	179	84	40
Subject 10	168	70	38

This research will develop a new set of body wear-based (wearable) biomechanical measures for gait characteristic study. The system used in this research includes video cameras and smartphone accelerometer sensors. The set of body wear is verified by calculating data from the accelerometer sensors embedded in the smartphone and digital camera data, and compares the data from the smartphone sensors and camera images data. Figure 3.1 shows the steps followed in the first part of the research methodology.

3.2.2 Research protocol

To develop and evaluate the idea of the first part of this research, 10 normal males aged between 25 and 35 years were recruited. Their weight was in the normal range (Body Mass Index falls within a weight range that is not associated with an increased risk for weight-related diseases and health issues) or 20kg overweight. They were fitted with a smartphone around the right leg. Each subject was asked to walk two steps at their normal walking speed, and data was gathered from each subject. At the beginning of the test, each subject turned on the program (inbox tool) manually and commenced walking, and the test data was recorded for each subject. The use of human subjects in this research was approved by the University of Southern Queensland Human Research Ethics Committee (No H20REA267).

3.2.3 Camera calibration and photogrammetric data capture

3.2.3.1 Camera calibration

Camera calibration is considered a vital stage in photogrammetric studies to improve the accuracy of the measured coordinates (x, y) of an image. For this reason, in this study, four JVC cameras were calibrated by finding the interior orientation parameters$\left(X_{0,}Y_{0,}\, F\right)$, radial distortion parameters (K_1, K_2, K_3) and lens alignment $(P_1, P_2, P_3\ )$ to obtain accurate results. The selected cameras were calibrated individually using a self-calibration technique (Remondino & Fraser 2006; Udin & Ahmad 2011) with an object distance of 900 mm as shown in Figure 3.2. The test-field used to calibrate the camcorders consisted of a grid of 10 rows and 10 columns of steel pins (100 pins in total) which were attached to a polycarbonate board of 12 mm thickness. The pins had different elevations ranging from 10 mm to 60 mm above the surface of the board, and retro-reflective targets of 5 mm diameter were attached on each pin. The RMS tolerance specified for the target coordinates were 0.05 mm across the X, Y and Z axes for each of the camcorders.

Calibration was also required as the lens parameter values were required for the subsequent photogrammetric application (Chong et al. 2008). In calibration, nine sets of convergent video clips of the test-field were captured from four different camera station positions, individual frames were extracted from the clips, and the frames were processed using the off-the-shelf camera calibration software, Australis®. Result of camera parameter after run the bundle in the Australis program are clarified in Appendix B2.

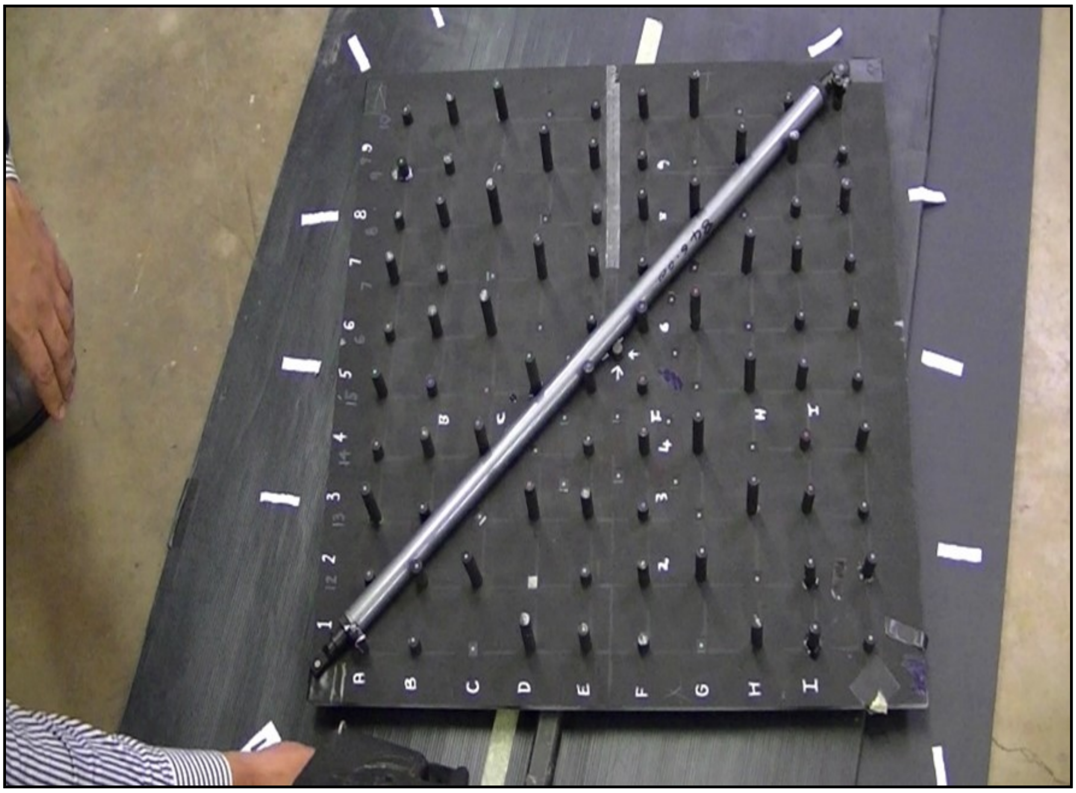


Figure 3.2: Camera calibration target board

The PLPC (Principle Lens Parameter Computation) technique (Chong 2011) was used to determine the lens parameters during an imaging session, as shown in Figure 3.3.

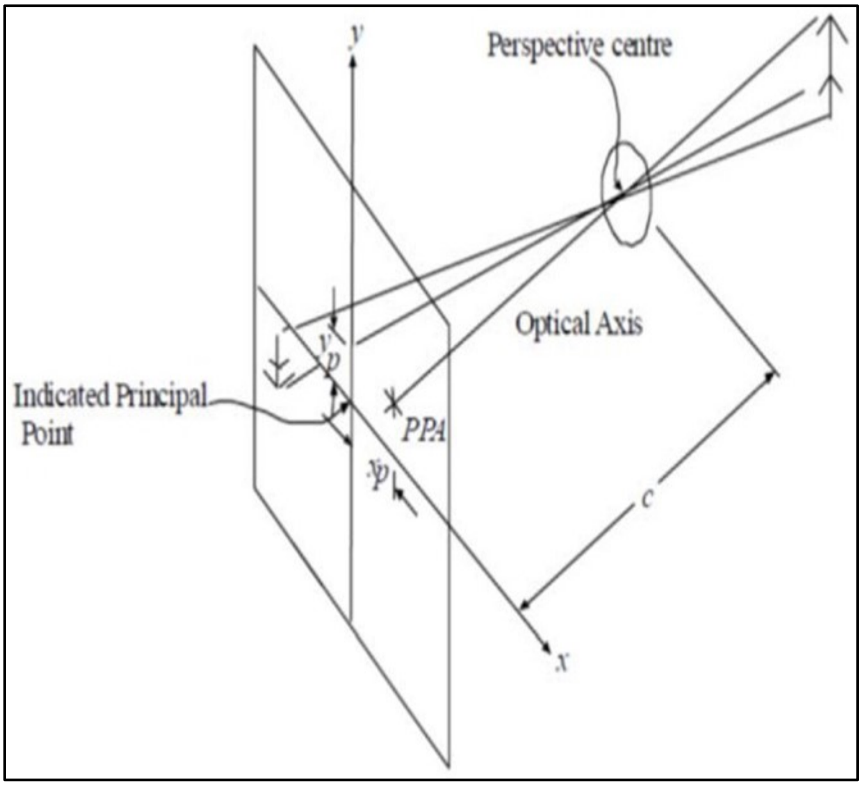


Figure 3.3: Focal length where xp and yp are the coordinates of a point in the camera coordinate system and c=focal length (Chong 2011)

3.2.3.2 Video camera recording data

Capturing video clips for the legs and thighs during gait was achieved using a close-range photogrammetric system (CRPS), as shown in Figure 3.4, using four HD Panasonic Lumix video cameras. These video cameras were utilised to extract clear frame (image) as related to the smartphone testing. The researcher converted the frames into 3D modelling to obtain the 3D coordinates of the target.

Figure 3.4: Four digital HD Panasonic Lumix cameras

3.2.4 Smartphone accelerometer calibration

Sensor calibration is a method of improving sensor performance by removing structure errors in the sensor outputs (Li et al. 2015). Many researchers have developed different calibration techniques for the proposed sensor output model. For example, Bekkeng (2009) evaluated gyro parameters through a Kalman filter using a computer controlled rate table and a homemade temperature chamber. Olivares et al. (2009) used a rotation plate and an automatic level topographic instrument.

In this research, the smartphone accelerometer sensor calibrations were achieved using a motion capture system. To reach the sensor calibration by motion capture system, optoelectronic cameras were used to collect 3D data. Ten Qualisys computerised motion analysis system (Qualisys 2.14, Gothenburg, Sweden) infrared motion cameras were utilised for testing at the Gait Laboratory at the University of Southern Queensland as shown in Figure 3.5. The MCS-based motion capture system is increasingly applied to the continuous indoor and outdoor ambulatory motion measurements in the daily life. Three cameras were positioned at the back of the walkway, three cameras at the front of the walkway, and two cameras on each side of the walkway. These cameras were designed to obtain the three-dimensional coordinates of the retro-reflective markers that were positioned on the smartphone screen. This calibration was started by putting one target on the smartphone screen at the same position of the smartphone accelerometer sensor and dropping the smartphone to the ground where the motion capture cameras captured it as seen in Figures 3.6 and 3.7. A motion capture system works with specific targets so we need to use this target to read the phone movement.

After that, 3D data was collected from both the smartphone sensor and the motion capture system. Qualisys Track Manager Software was used to collect the 3D data of the motion capture system. Qualysis track manager setting up process and specifications described in Appendix B1.

Figure 3.5: Setup of motion capture system

3.2.4.1 Correlation sensor and motion capture system data

In this work, the sensor data during movement should be the same as the data that comes from the motion capture system (MCS). However, the first frame in the sensor reading (Xs, Ys, Zs) will not be the same as the first frame (MCS) (Xc, Yc, Zc) because the start time measurement is different. The sensors' coordinates will be generated from the output measurements of MCS as shown in Figure 3.8. The 3D Conformal Transformation method was adopted as the mathematical method to connect both systems.

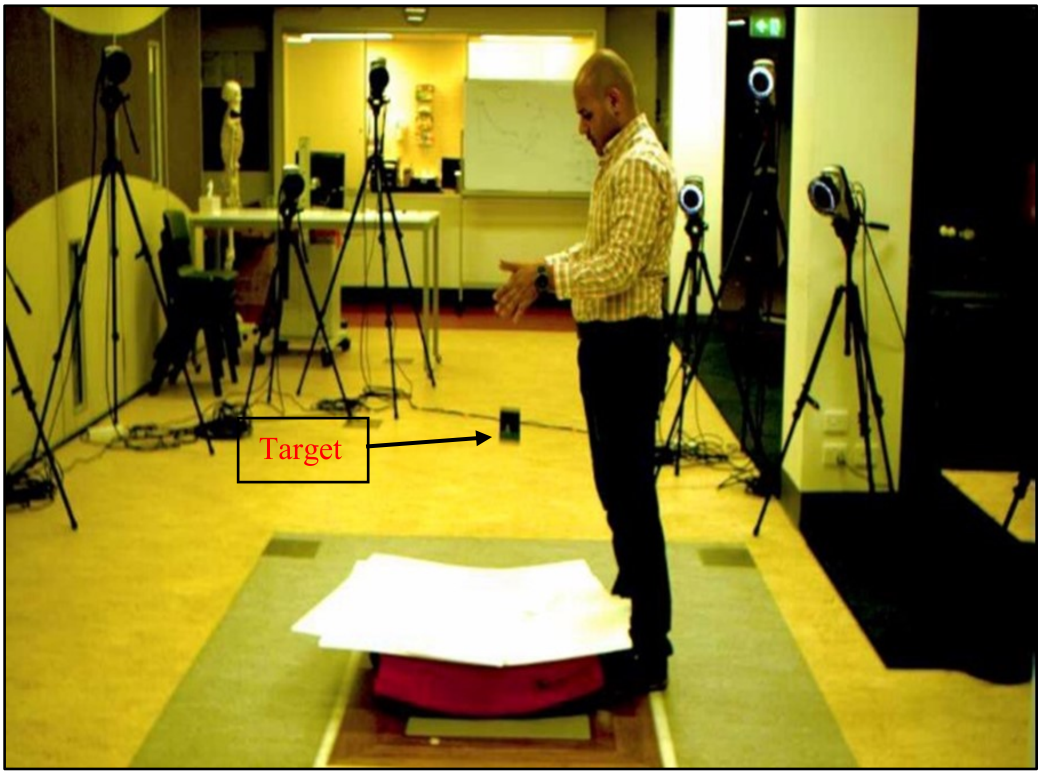


Figure 3.6: Motion capture system with side view capture

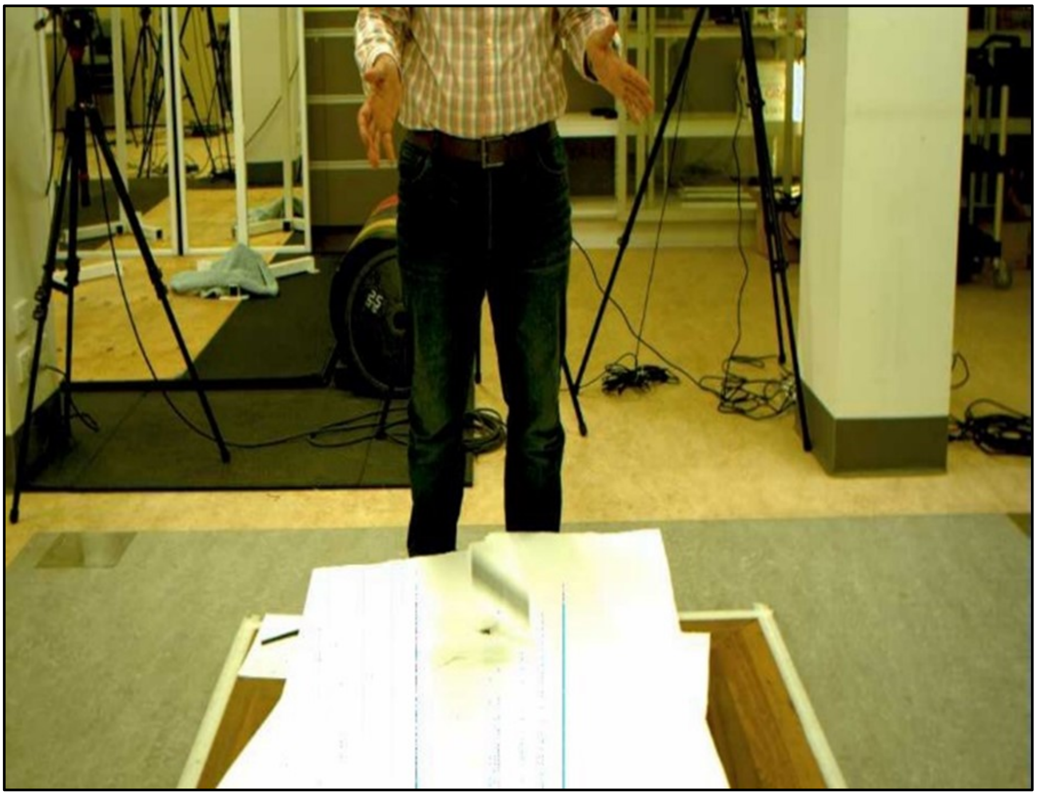


Figure 3.7: Motion capture system with front view capture

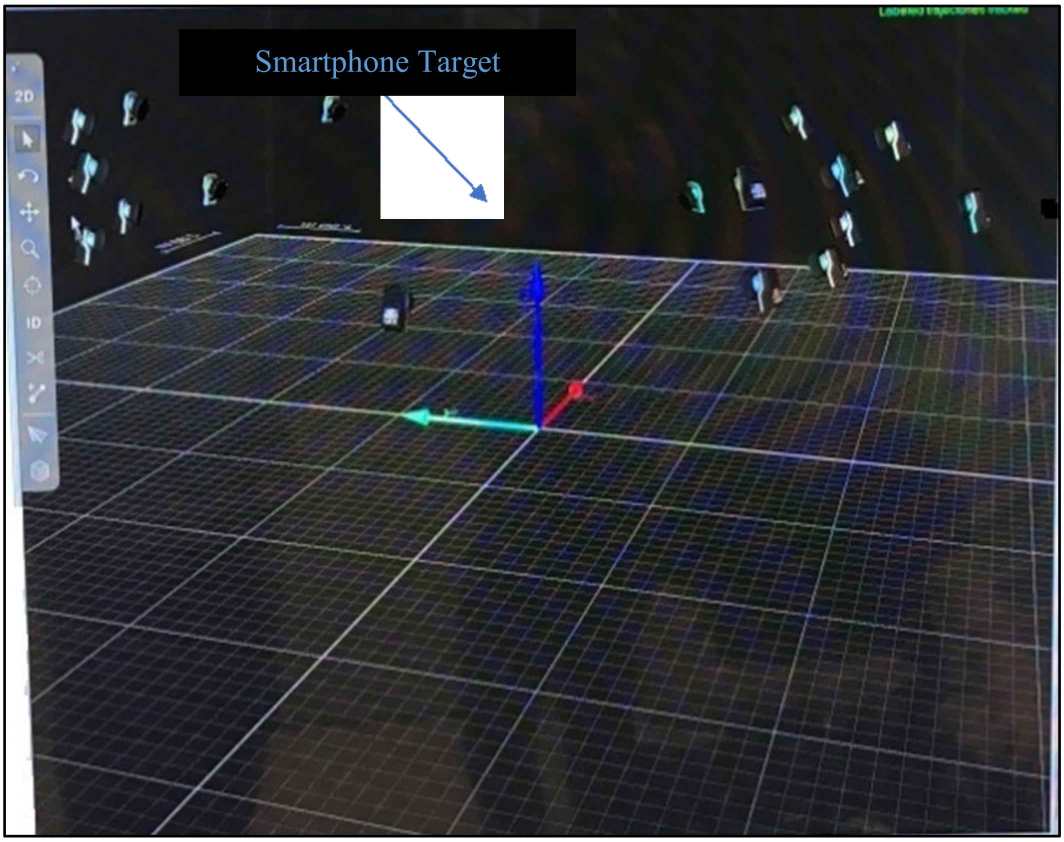


Figure 3.8: Motion capture system simulated sensor

3.2.5 DATA ACQUISITION

The data was stored on an Android phone and analysed offline through the extraction of features in time and frequency. The current study employed a smartphone sensor accelerometer. This sensor was located next to the lower limb of the body; the right leg of each subject's body. Smartphones were placed there because "the human body is made out of numerous exceedingly adaptable fragments, and the upper body movement of people is particularly complicated as far as precision estimations" (Liu et al. 2007). Accelerometer data was measured by a tri-axial which provided simultaneous measurements in three orthogonal directions for analysis of all of the vibrations being experienced by a structure. These sensors were located on the front side of the leg in front of the camera as presented in Figure 3.9 A and B. In addition, smartphone sensors can provide a variety of valuable data. For instance, a device can recognise a subject's physical activity, such as walking or running, by analysing accelerometer data. This information can be collected over a period to identify daily habits.

Figure 3.9 A and B shows the collected camera data. Two photogrammetric control boards were installed at the left and right of the floor mat to provide a control for the camera resection with scaling. The coordinates of the target in the two boards were calculated with a bundle adjustment technique. The captured digital images of the different dimensions of the calibration plate were downloaded to a PC with Australis software (v 6.06). This method enabled calibration, avoidance of lens distortion errors and determination of foot axis using a bundle adjustment.

These data were recorded when the red light installed in the right board and connected to the sensor in the floor mat (as displayed in Figure 3.9 A) came on. To increase the accuracy of the synchronization time between the smartphone, camera and floor mat we used a timer plus the light as shown in Figure 3.9 B. Data collection began when the heel-down portion pressed on the floor mat and continued until the toe-off portion of the gait. Appendix B3 illustrates the 25 photographs of one step for one subject from one camera only from the heel strike to toe off.

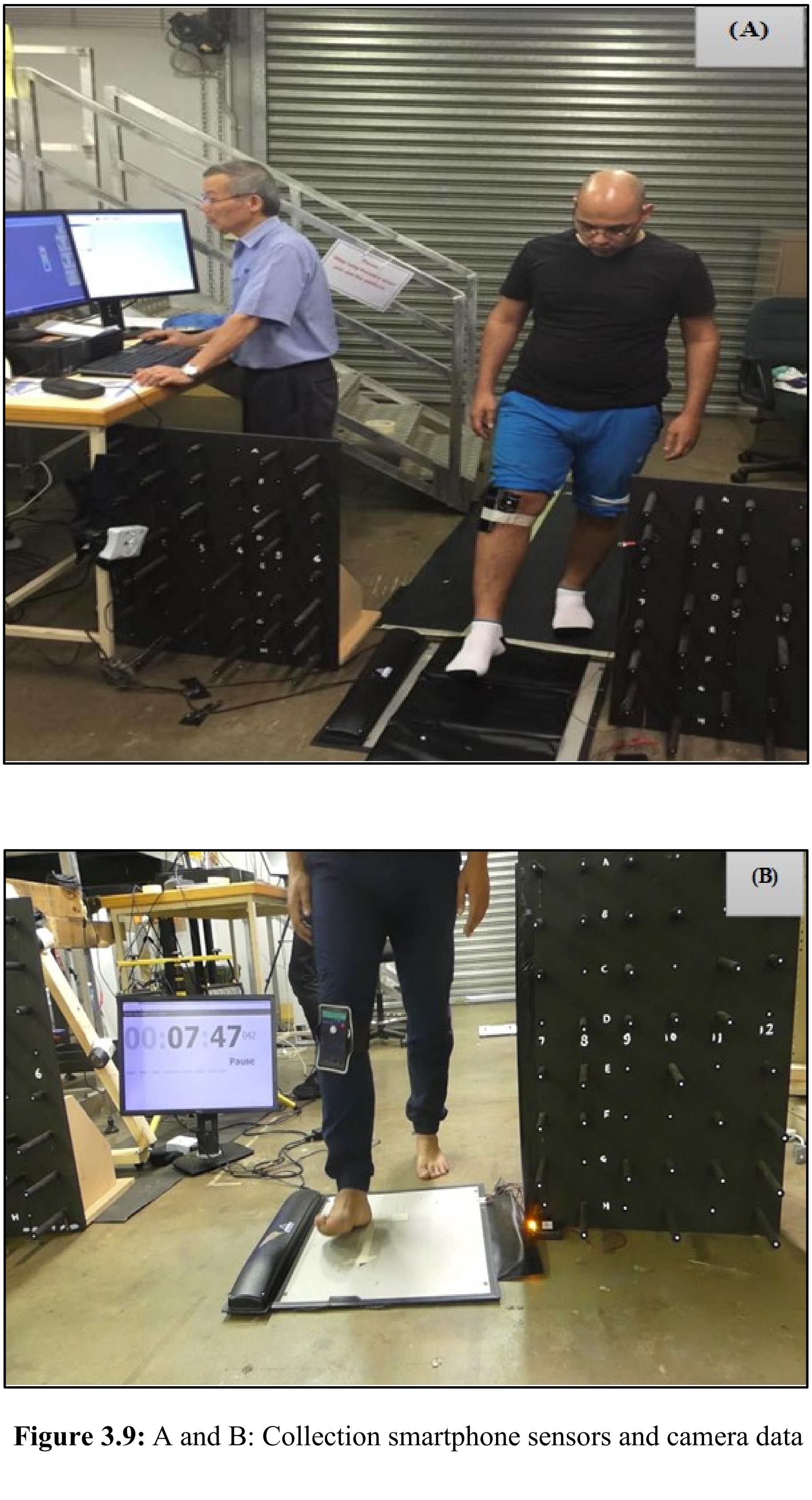


Figure 3.9: A and B: Collection smartphone sensors and camera data

3.2.5.1 Accelerometer sensor data

Accelerometer sensors measure the acceleration forces acting on an object in order to determine the object's position in space and monitor the object's movement. To collect data, an accelerometer analyzer application was used to capture the accelerometer data. This application provided the speed, which was 50Hz in this research. It also provided the x-axis, y-axis and z-axis. These axes represent the horizontal/sideways movement of the participant (x-axis), upward/downward movement (y-axis), and forward/backward movement (z-axis). Figure 3.10 explains these axes which are related to a subject. Each accelerometer axis provides a signal which provides a frame. Every test was labeled with subject’s name and test’s time. In this research we used the positive peak in the acceleration signal in the interior-posterior direction as the instant of heel contact (Brandes et al. 2006).

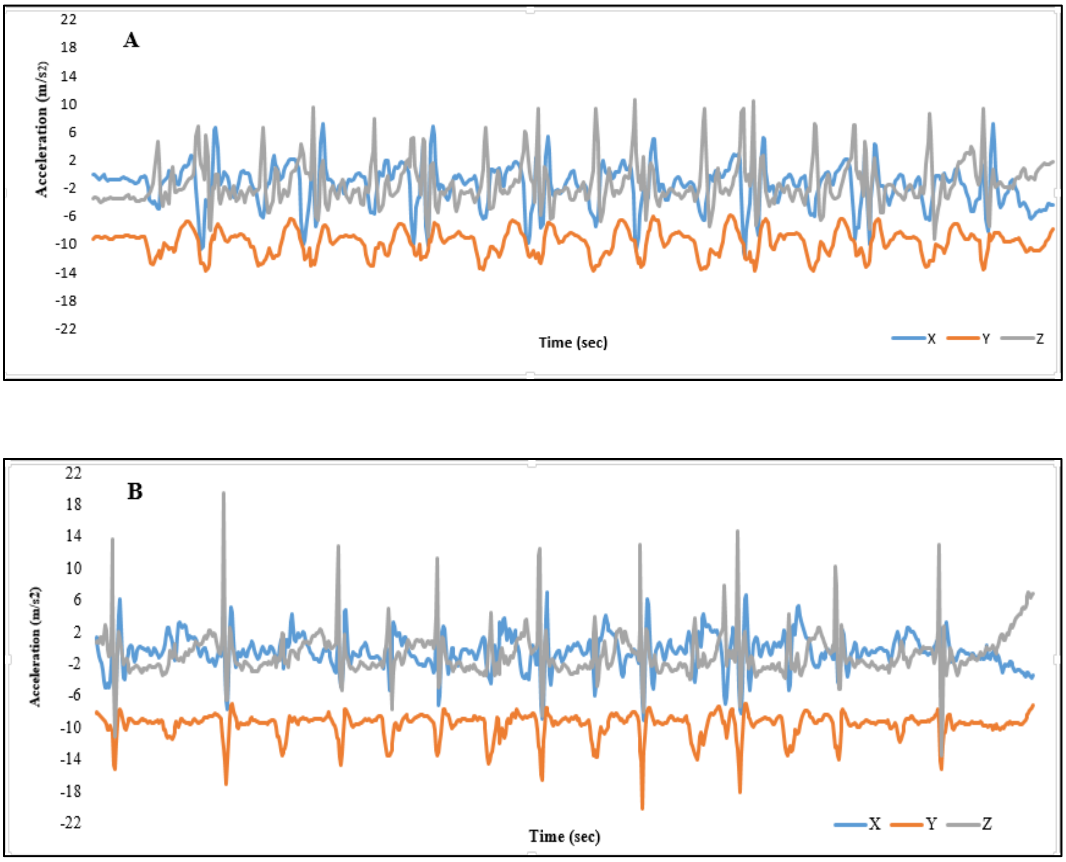


Figure 3.10: Sample acceleration signals for walking. Normal gait (A) and disability gait (B)

3.2.6 Experimental measurements and analyses

Investigation involved measuring the motion gait of a participant's leg during a movement, and determining the type and accuracy of data obtained from the sensors. Depending on the idea of this research, it can be divided into two phases. First, the researcher compared data obtained from the camera and sensor to evaluate the accelerometer measurement. Four Panasonic Lumix cameras were used to record participants' movements. Therefore, images were extracted from video cameras. These images were converted into 3D modelling to obtain the 3D coordinates of targets (Xc, Yc, Zc). The other device, sensors embedded in smartphones, provided three coordinates (Xs, Ys, Zs). Throughout the gait cycles, several frames were created depending on the sensor readings. Despite the limitations of this research in synchronising sensors with digital cameras and using commercial sensors, the preliminary results suggested that the implementation of sensor measurements was indeed feasible. The following steps of Experiment 1 included:

1- Fix the target on the smartphone
2- Fix the smartphone to the subject's leg
3- Calibrate the camera
4- Let the subject walk
5- Record the data from cameras' sensors
6- Analyse and evaluate the data.

3.3 Temporal spatial parameters

3.3.1 Overview

Spatiotemporal gait parameters are related to adverse health issues such as risk of fall (Kalron & Achiron 2014; Bang & Shin 2016). Recently, gait analysis researchers have used different instruments to evaluate gait parameters to study the risk of falling. Several technologies utilise insoles for specially designed shoes (Howell et al. 2013). An insole sensor was shown to be suitable to determine human movement parameters such as the stance and swing phases (Martínez-Martí et al. 2014). The insole sensor is also able to measure a number of spatiotemporal gait parameters: swing time, stride length, step time and cadence (Noshadi et al. 2014). Other studies using insole pressure sensor data enabled the planning of ways to reduce plantar pressure among diabetic patients (Zequera & Solomonidis 2010).Thus, the purpose of the second part of the research methodology was to: 1) investigate two smartphones in determining spatiotemporal gait parameters (step time, stride time, cadence and walking speed) and 2) evaluate the validity of a smartphone-based tri-axial accelerometer to assess gait characteristics. The second part of the research methodology is outlined in Figure 3.11.

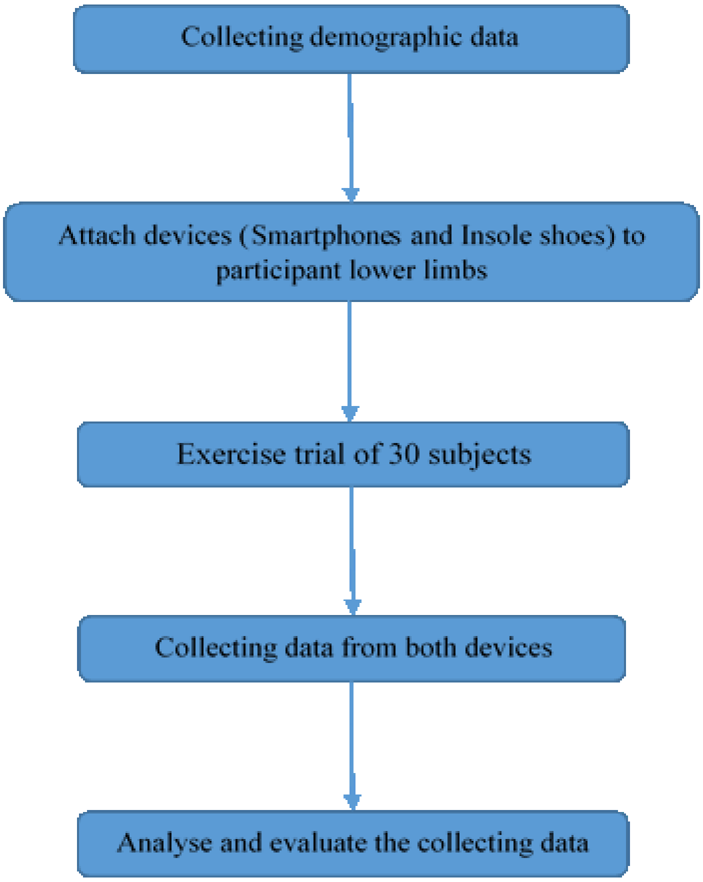


Figure 3.11: Research methodology outline (second part)

3.3.2 Equipment

To perform the second part of our research we used two types of equipment (two insole sensors and two smartphones Samsung S9).

3.3.2.1 The plantar pressure measurement system (insole sensors)

The plantar pressure measurement system is comprised of:

a- 3000E F-scan in-shoe sensors sampling at 100 Hz to capture COP excursions in the anterior-posterior (AP) and mediolateral (ML) directions as shown in Figure 3.12. From these, contact area, direction of sway, distance, direction travelled by the COP, and variability of distance travelled by the COP was obtained using F-Scan Research ver. 6.70-03 software

b- Small size and 0.5 mm thickness force pressure sensors were used to measure the load between the ground support and human foot (Noce 2005; Rana 2009) as shown in Figure 3.13. These thin sensors are sufficient to enable non-intrusive measurements and are ideal for measuring the forces and pressure without testing the dynamics of the subjects. Appendix C1 provides more details about the insole sensor specification.

In this research Force Resistance Sensors (FRS) were selected due to their electronic simplicity, inexpensiveness, moderate accuracy (better than $\pm$ 5% of full use force (780 kPa)) and ability to observe the load of the foot during gait (slow or fast walking and running) (Noce 2005).

Figure 3.12: Insole sensor

Figure 3.13: In-shoe pressure system

3.3.2.2 Smartphone Samsung S9

As shown in Figure 3.14, the Samsung Galaxy S9 has a height of 5.81” (147.7 mm), width of 2.7” (68.7 mm), depth of 33” (8.5 mm), weight of 163 g and screen size of 5.8” (147.3 mm). The application used in our research was inbox tools as shown in Figure 3.15.

Figure 3.14: Samsung Galaxy S9

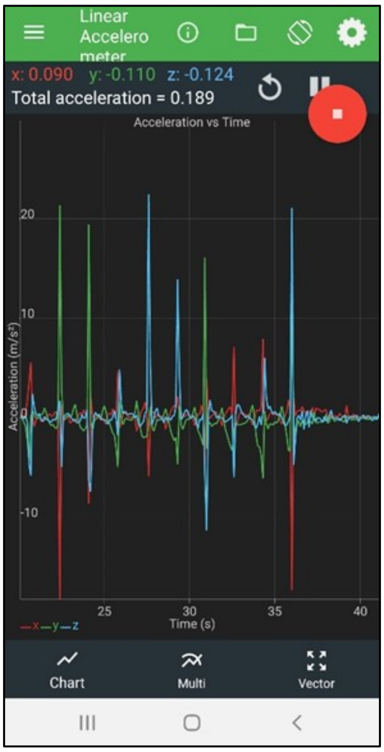


Figure 3.15: Physics tool app with linear accelerometer reading

3.3.3 Participants

In the second part of this research, 20 healthy adult subjects aged between 20 and 40 years were recruited. Their mass and height were 60 to 95 kg and 156 to 180cm, respectively, as presented in Tables 3.2 and 3.3. All walked continuously for at least 10 meters without help or assistance devices. Some demographic properties were obtained from each participant: age, gender, height, weight and shoe size. All subjects gave written consent at the beginning of the trials. A human ethics application was approved by the Human Research Ethics Committee at the University of Southern Queensland (No H20REA267).

Table 3.2: Demographics for group of 10 males

Participants	Height/cm	Weight/kg	Age
Subject 1	176	80	45
Subject 2	185	100	42
Subject 3	173	90	36
Subject 4	171	93	33
Subject 5	178	81	30
Subject 6	177	82	30
Subject 7	176	71	34
Subject 8	174	81	35
Subject 9	179	84	40
Subject 10	168	70	38

Table 3.3: Demographics for group of 10 females

Participants	Height/cm	Weight/kg	Age
Subject 1	159	62	19
Subject 2	168	50	22
Subject 3	164	69	24
Subject 4	168	69	27
Subject 5	164	29	25
Subject 6	165	69	23
Subject 7	166	68	27
Subject 8	168	64	24
Subject 9	169	60	23
Subject 10	170	55	21

3.3.4 Data collection and processing

After consent, the subjects were asked to walk along a 10-meters long walkway for a short warm-up trial. Before recording of the trial, each participant was given three minutes to practice the procedure, thus minimising walking errors without alteration of step characteristics. Data were collected for the gait spatiotemporal parameters: step time, stride time, cadence and walking speed. In the trial, the participant was shown a standard gait procedure from standing position to stepping onto the floor using the 3000E F-scan in-shoe sensors sampling at 100 Hz. After inserting the 3000E F-scan in-shoe sensors inside the subject’s shoes (Figure 3.16) five walking trials were recorded for each subject. Nine steps were collected per straight-line walk for each of the five trials. In order to collect high accuracy plantar pressure data, the average of the three middle steps was taken from the nine steps for each trial, see Figures 3.1.7 and 3.1.8. The best trial recordings were chosen for processing using F-scan research software. In other words, we choose the clearest outcome data from the insole sensor after check the reading stable.

Figure 3.16: A and B: An example for two people wearing insole sensors and smartphones during the test

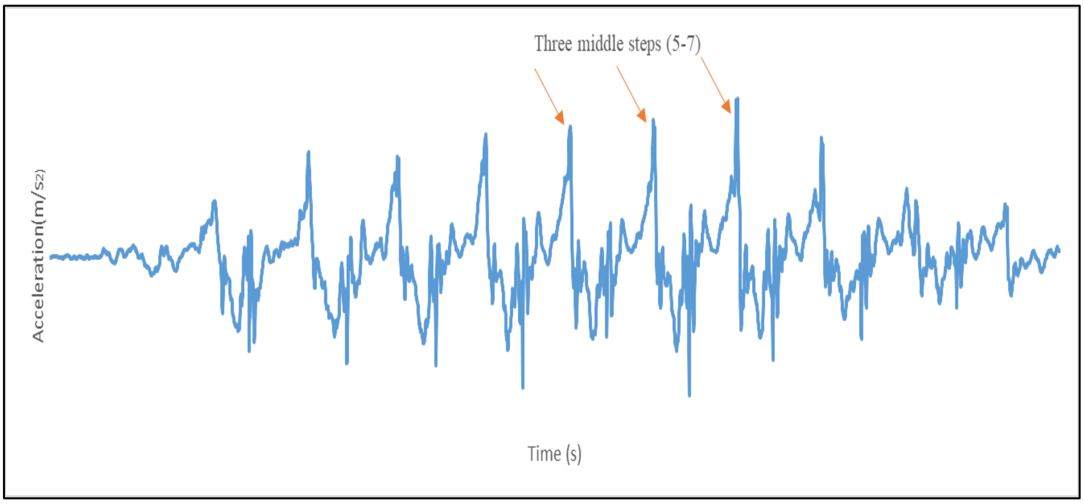


Figure 3.17: Trial with nine steps of the accelerometer for one subject

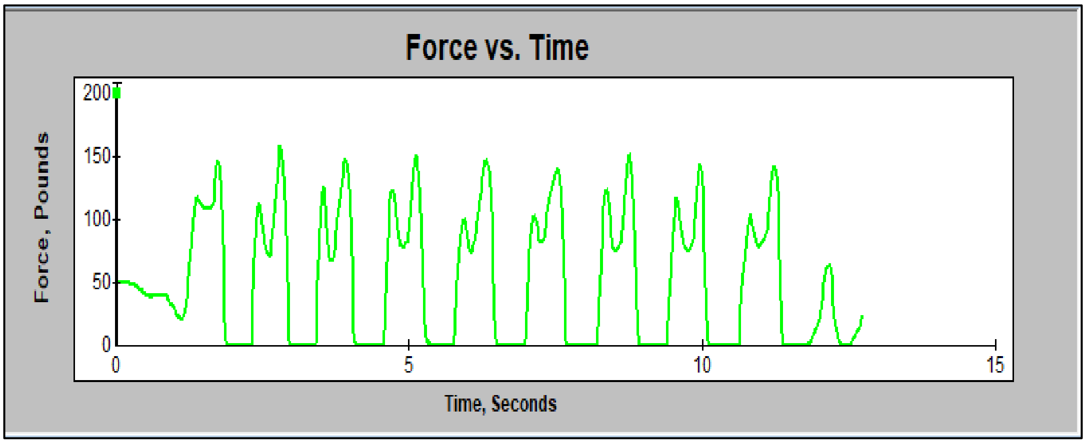


Figure 3.18: Nine steps from F-scan of insole sensor

The smartphone was attached to each subject's lower limbs in order to collect spatial parameter data. The tests were completed and the data were collected simultaneously for both the smartphones and insoles sensors. The differences were detected, and some basic features of both patterns for the insole sensor and accelerometer sensor could be observed. First, the insole pattern in forward and upward directions was more stable most of the time because its work depended on the leg pressure sensor. For the smartphone, the pattern showed more stable steps in 5-7 (as shown in Figure 3.17) because the accelerometer data depended on the walk. In other words, acceleration change was small at the beginning and end of walking.

Moreover, the smartphone accelerometer forward and upward directions data show some noise and negative signals in the pattern, but we used the positive signals only.

The change of sign of the positive peak in the acceleration signal in the anterior-posterior direction was taken as the instant of the foot contact Ducharme et al. (2018). In steps time and stride time the data calculated the average of the time for the three middle steps (5-7) steps. The time of these three steps was added and divided by 3, and the same was done for stride time but for three strides. The processing of cadence was calculated based on the equation stated in the work of Silsupadol et al. (2017). The walking speed was computed by dividing the distance along the entire walkway over the time. Finally, to validate the accelerometer's ability to detect the number of steps, the subject walked nine steps depending on the lap distance on a flat floor indoors with no obstacles nearby.

3.3.5 Statistical analysis

A repeated measure analysis of variance (ANOVA) was used with the four factors with a post-hoc Bonferroni correction to determine statistical differences (mean differences) between each two factors (conditions). The P value would be significant if it was less than 0.025, according to the analytical regression equations of (Perneger, 1998).

Mean, standard deviation and interclass correlation coefficient measures were applied in this study to evaluate the performance of the proposed method. Those measures were computed for each subject's trials and then the average of the mean, standard deviation and interclass correlation coefficient were collocated. Interclass correlation coefficients (ICC) using for comparison between the two systems for all four parameters.

Blind-Altman plots were used to provide the bias and limit of agreement (LOA) between smartphone sensor and insole sensor data, as well as to evaluate the developed study method.

To assess the validity between the insole sensors and smartphones for each trial, the Pearson correlation was also used in this analysis. To investigate the effectiveness of the smartphones as opposed to the insole sensors in determining spatiotemporal gait parameters (step time, stride time, cadence and walking speed), box plots were used based on the Pearson correlation coefficient. The box plots consist of three parts:

upper, lower and middle. The upper part of the plot box denotes the 75th percentile, the lower part denotes the 25th percentile, while the central part refers to the median 50th percentile which is sometimes called the centre.

For further evaluation of the study, the behaviours of the smartphones and insole sensors were analysed and tested for spatiotemporal gait parameters using R-squared (R^2).

3.4 Summary

This chapter demonstrates a new developed methodology for conducting human gait analysis. It also introduces new protocols for collecting gait accelerometer measures, photogrammetry images and spatiotemporal data with higher accuracy. This research illustrates how to determine and evaluate smartphone accelerometer technology to replace current photogrammetry techniques using imaging sensors. It also illustrates how to collect and process the data of spatiotemporal human gait parameters for four devices (two smartphones and two insole sensors) of different groups using a cohort of 30 adults. Finally, this chapter explained the experimental measurement and analysis of the first and second parts of this research.

CHAPTER 4: TRIAL RESULTS AND ANALYSIS

4.1 Introduction

Human movement and gait characteristics have been studied using a variety of devices such as cameras and pressure and force sensors. These devices, however, have some disadvantages such as cost of purchase, space requirements and processing time. Scientists are currently interested to develop new measurement methods based on advanced electronic technology.

This chapter presents the results of the research based on the methodology introduced in Chapter 3. The first part of this chapter represents the achievement of the first objective (to which we referred in Chapter 1). The accelerometer measurements obtained from smartphone devices and new camera and smartphone sensor measurement data results are presented in Section 4.2. These results achieve Objective 1. They validate the accuracy of the presented method. Vertical distance was measured during the main phases of gait from heel strike to toe-off. An analysis and comparison of the photogrammetry, accelerometer and floor mat sensor data shows that it is more accurate and that this accuracy is significant.

The second part of this chapter presents the results of the new methodology for the smartphone sensor device to analyse spatiotemporal gait parameters to achieve Objective 2. We investigated the use of two smartphones to determine spatiotemporal gait parameters (step time, stride time, cadence and walking speed) by collecting spatiotemporal human gait parameter data with four devices (smartphones and insole sensors) for different groups using a cohort of 30 adults. To achieve the third and fourth research objectives we determined the effectiveness of the characteristics of the gait parameters to identify the relationship between smartphone and insole sensors and used different statistical methods to evaluate the performance of the proposed method. All statistical analyses were performed using SPSS Version 24 and Excel 2010.

4.2 Evaluating smartphone accelerometer for existing and new measurement

Smartphone accelerometer and camera data were record and computed based on the method explained in part one of the methodology chapter. The researcher tested the sensors by choosing an application to capture sensor data of speed, accuracy and types of file to make the analysis of data easier and quicker. Also, the researcher found the accelerometer data may affected by the mounting of the sensor depends on the sensor model. For that, different examine have been achieved in this research to check the ability of the smartphone sensor to recognise the gait parameters. Next, the researcher tested the accelerometer by putting a smartphone on the leg of an individual who then walked. At the same time, digital cameras were used to record the individual walking.

It is not clear if the inconsistency in data verification is affected by the walking activities or by the mounting of the sensor.

In this test we used 10 frames for each subject's gait, and the results show that the output data for both the sensors and the cameras are almost the same: Figures 4.1, 4.2 and 4.3. Each figure represents the target movement for each step, starting from the heel strike and ending in the toe off. The distance between the heel strike and tow off is calculated using equation (1)

$$D = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \quad \text{.........} (1)$$

D=distance
(x_1, y_1) =coordinates of the first point
(x_2, y_2) =coordinates of the second point

Regrading to the above equation the outcome showed five frames as shown in Figurers (4.1-4.3). The aim was to experiment new technique throughout testing fewer subjects. The following results were mainly focused on measuring position and distance in x and y direction of the frontal plane.

In the following figures we see good agreement between the accelerometer data and photogrammetry data. In terms of knee movement, each subject has a different movement form heel strike to toe-off. In Figure 4.1 shows the high agreement in the first movement but start to be slightly different when the subject move. Notably, Figure 4.2 shows a distinct difference from starting with a step whilst still the same movement for both readings (photogrammetry and accelerometer sensor). This could be because of the synchronization of movement initiation for both devices so the camera captures data before the smartphone accelerometer. The figures below show the consistency of the obtained results, with each of the following figures representing one subject. The accelerometer and photogrammetry show that the vertically measured distance was approximately similar.

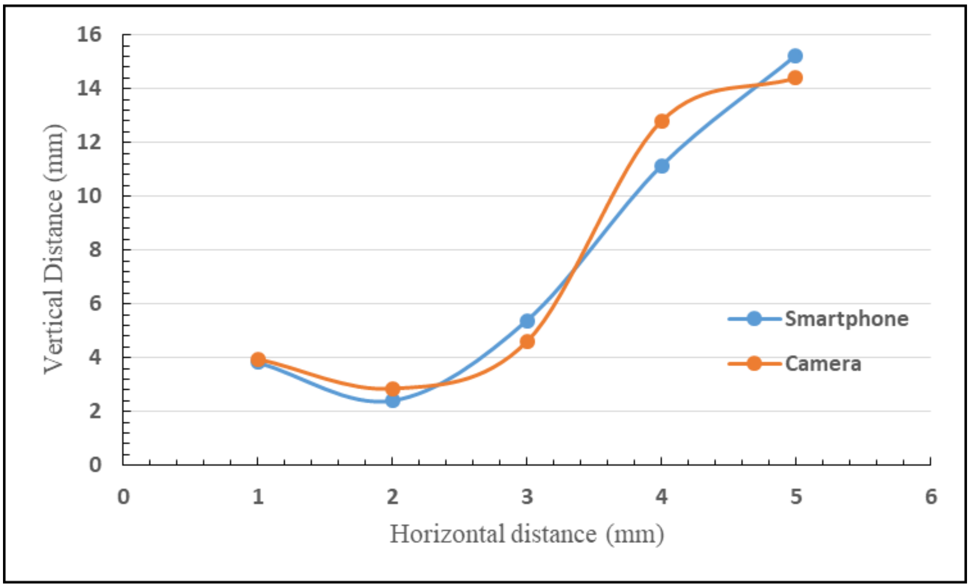


Figure 4.1: Subject 1 accelerometer sensor data versus photogrammetry data

For the third participant, we can see the high agreement between both readings in the phases of complete step (Figure 4.3).

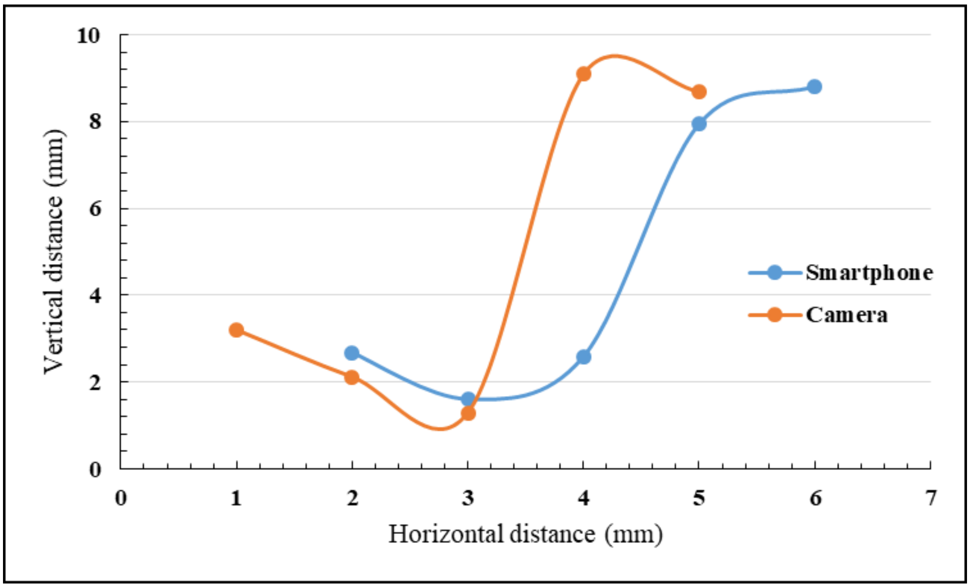


Figure 4.2: Subject 2 accelerometer sensor data versus photogrammetry data

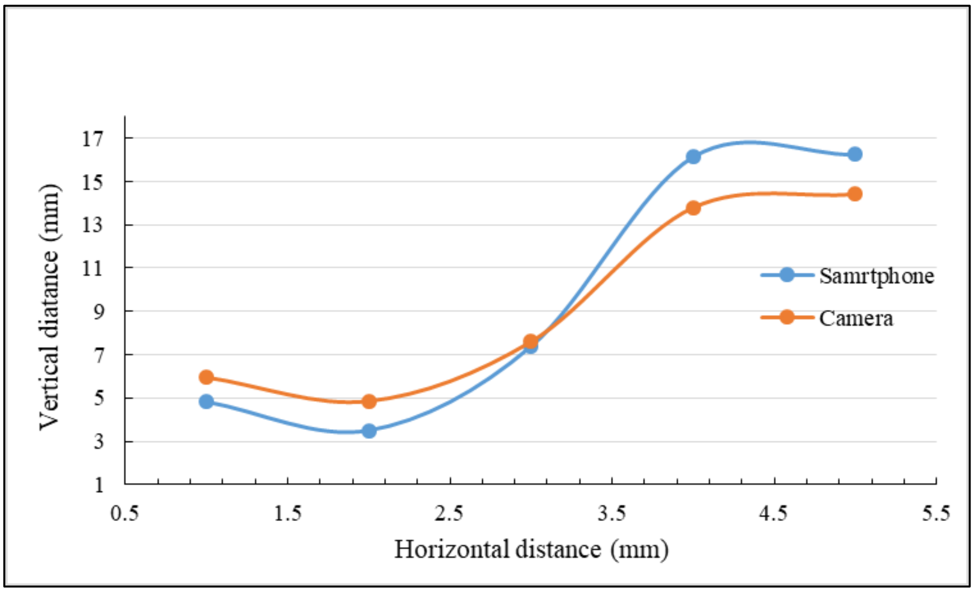


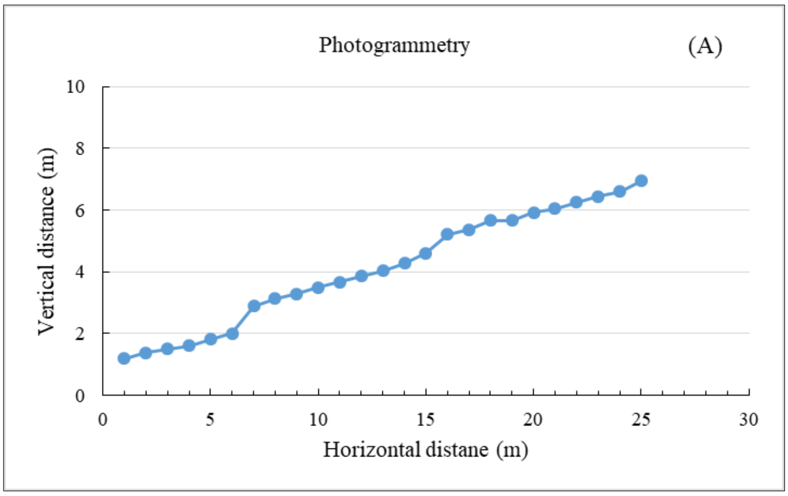
Figure 4.3: Subject 3 accelerometer sensor data versus photogrammetry data

To further validate the accuracy of our technique, 10 healthy males, with no issues that could in any way affect their gait, were recruited for study in gait phases from heel strike to toe-off. The trials were recorded for each person and the results (mean and standard deviation) of the right foot are displayed in Table 4.1.

The 25 frames of gait were divided into five phases (heel strike, loading response, midstance, heel-off, and toe-off) and the number of frames between each two phases were different according to limb position. Figures 4.4 to 4.13 represent the knee movement for each subject (each figure is comprised of two parts: A and B). A provides camera photos extracted from the video for each subject's movements. Each spot in the figure represents the 3D coordinates of the target. B represents the accelerometer sensor reading frames of the smartphone.

The mean, SD and R values for heel strike, loading response, midstance, heel-off and toe-off for each subject are summarized in Tables 4.1 to 4.10. Heel strike, loading response, midstance, heel-off and toe-off stride from the two devices gave excellent agreement (R value >0.90) in most of the results.

For Subjects 1 and 2, the heel strike phase shows less agreement between the photogrammetry and accelerometer data, but the agreement increases until the toe-off phase (Figure 4.4 A and B and Figure 4.5 A and B). Figure 4.6 A and B represent Subject 3's data and shows less agreement in loading response, heel–off and heel strike (R= 0.63, 0.75 and 0.78) respectively as shown in table 4.3. Subject 4's data results show high agreement between both data (R> 0.87) in all phases except the Midstance (R=0.73), see Figure 4.7 and table 4.4. Furthermore, Figure 4.8 represent the movement of subject 5 and it shows less agreement in the heel strike phase where (R= 0.75) table 4.5, but subject 6 has less agreement in heel-off as shown in table 4.6 . For Subjects 7 and 10, the data shows high agreement with (R ≥ 0.89) in all phases. See Figures 4.10 and 4.13, and Tables 4.7 and 4.10. Only the heel-strike and Midstance phases showed less agreement (R= 0.68 and R=67) in subject 8, while in Subject 9 (R> 80) in all phases as shown in table 4.9. All the above results show some differences in agreement between the photogrammetric and accelerometer obtained data in some phases such as heel strike, Midstance and loading response, which may be due to the way of walking or the gait posture.



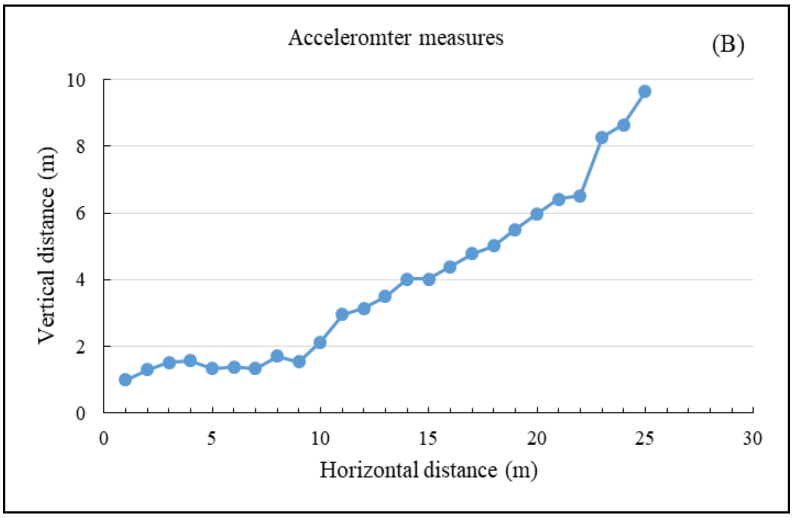


Figure 4.4: 25 frames for photogrammetry (A) and accelerometer measures (B) for first subject.

Table 4.1: Correlation between photogrammetry and accelerometer measures in the load phases of gait for first subject.

Variables	Photogrammetry technique (m)		Accelerometer measure(m)		R
	Mean	SD	Mean	SD	
Heel strike	1.50	0.21	1.35	0.21	0.64
Loading response	2.96	0.52	1.62	0.28	0.87
Midstance	4.08	0.32	3.53	0.44	0.90
Heel off	5.57	0.25	5.13	0.56	0.91
Toe off	6.45	0.31	7.89	1.25	0.95

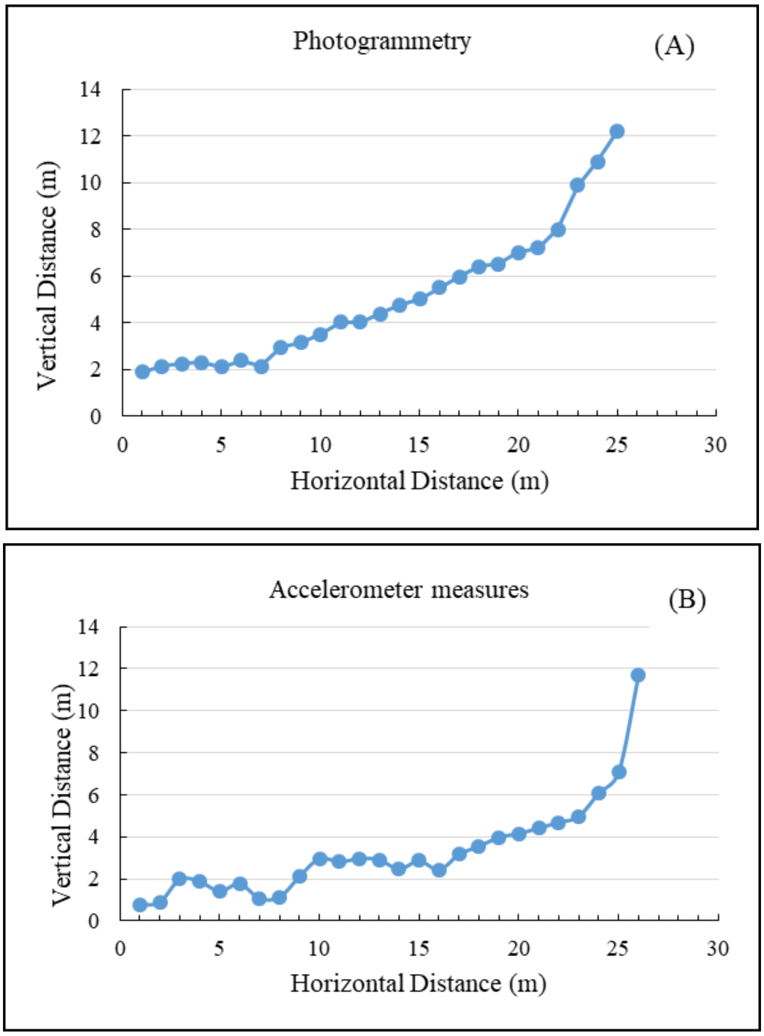


Figure 4.5: 25 frames of photogrammetry (A) and accelerometer measures (B) sensors for second subject.

Table 4.2: Correlation between photogrammetry and accelerometer measures in load phases of gait for second subject

Variables	Photogrammetry technique (m)		Accelerometer measure (m)		R
	Mean	SD	Mean	SD	
Heel strike	1.91	0.48	1.38	0.50	0.75
Loading response	2.54	0.43	1.21	0.28	0.83
Midstance	4.14	0.42	1.24	0.38	0.94
Heel off	5.89	0.56	2.26	0.21	0.99
Toe off	8.60	1.53	4.99	1.43	0.98

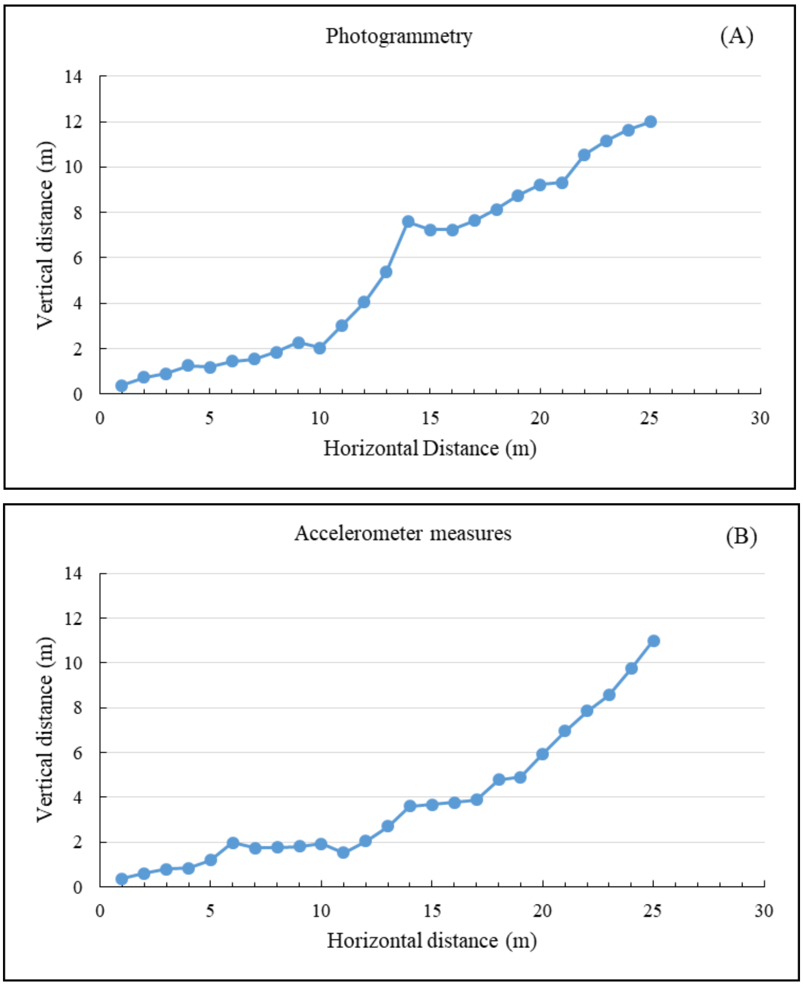


Figure 4.6: 25 frames of photogrammetry (A) and accelerometer measures (B) sensors for third subject

Table 4.3: Correlation between photogrammetry and accelerometer measures in load phases of gait for third subject

Variables	Photogrammetry technique (m)		Accelerometer measures (m)		R
	Mean	SD	Mean	SD	
Heel strike	0.76	0.31	0.68	0.32	0.78
Loading response	2.10	0.21	0.88	0.11	0.63
Midstance	5.46	1.77	2.70	0.86	0.83
Heel off	8.20	0.72	3.39	0.09	0.75
Toe off	9.79	1.69	6.40	1.29	0.94

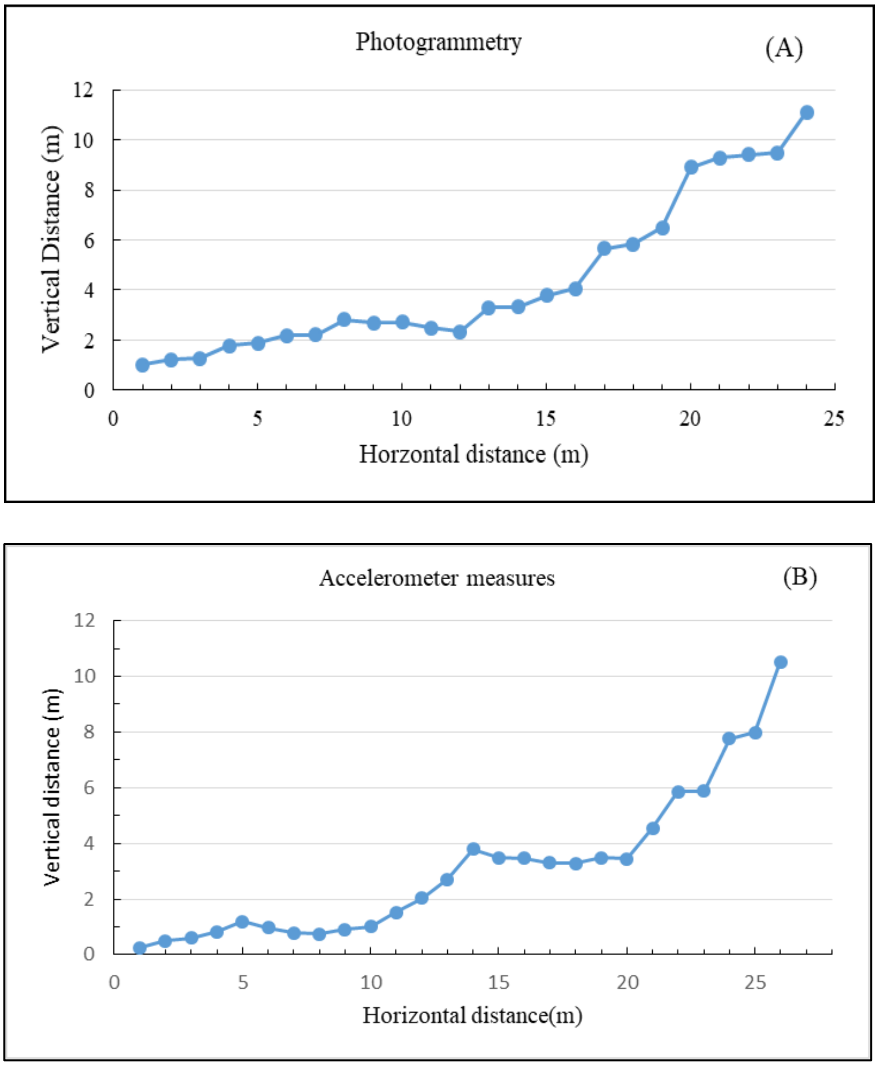
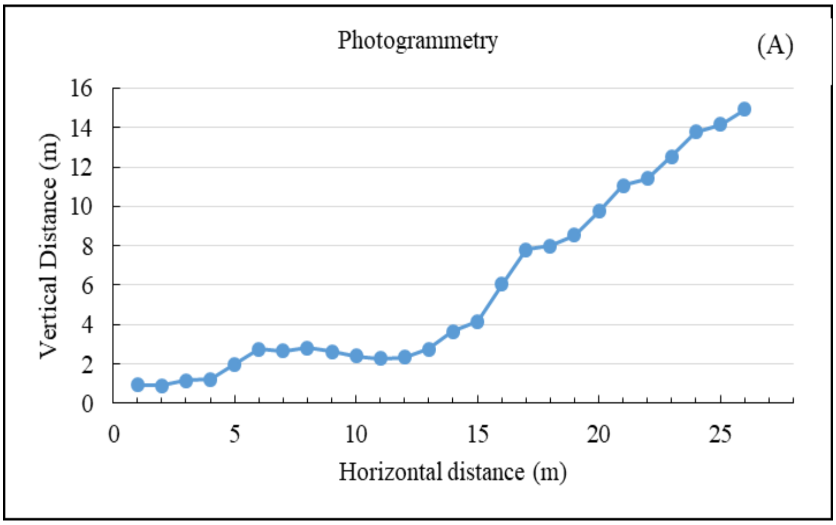


Figure 4.7: 25 frames of photogrammetry (A) and accelerometer measure**s** (B) sensors for fourth subject.

Table 4.4: Correlation between photogrammetry and accelerometer measures in load phases of gait for fourth subject

Variables	Photogrammetry technique(m)		Accelerometer measures(m)		R
	Mean	SD	Mean	SD	
Heel strike	1.44	0.34	0.92	0.26	0.96
Loading response	2.66	0.42	0.92	0.30	0.88
Midstance	2.77	0.92	2.20	0.82	0.73
Heel off	6.48	2.10	6.17	1.41	0.95
Toe off	9.20	1.10	6.83	0.48	0.89



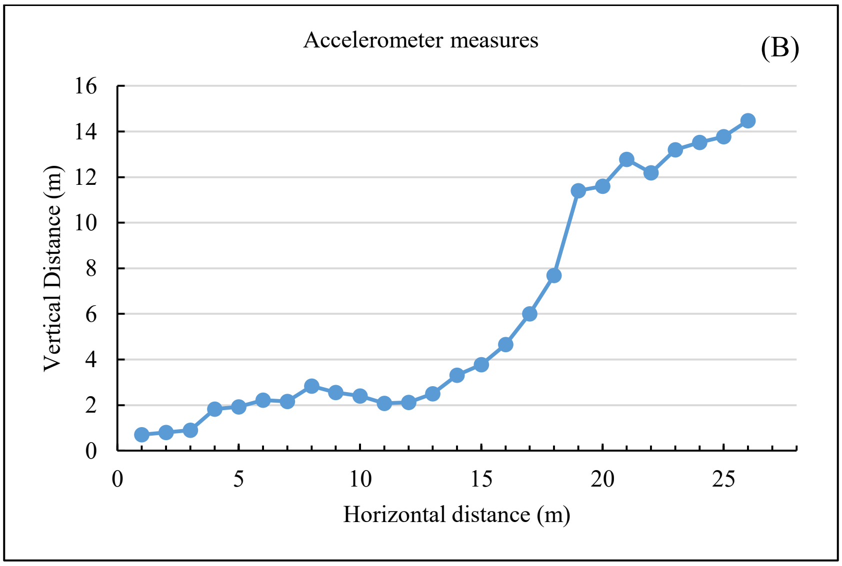


Figure 4.8: Vertical and horizontal positions for 25 frames of photogrammetry (A) and accelerometer measures (B) for fifth subject.

Table 4.5: Correlation between photogrammetry and accelerometer measures in load phases of gait for fifth subject.

Variables	Photogrammetry technique(m)		Accelerometer measures(m)		R
	Mean	SD	Mean	SD	
Heel strike	1.24	0.39	1.15	0.49	0.75
Loading response	2.52	0.23	2.15	0.41	0.88
Midstance	3.03	0.74	2.76	0.67	0.98
Heel off	8.04	1.20	8.27	2.81	0.83
Toe off	12.58	1.23	12.89	0.55	0.96

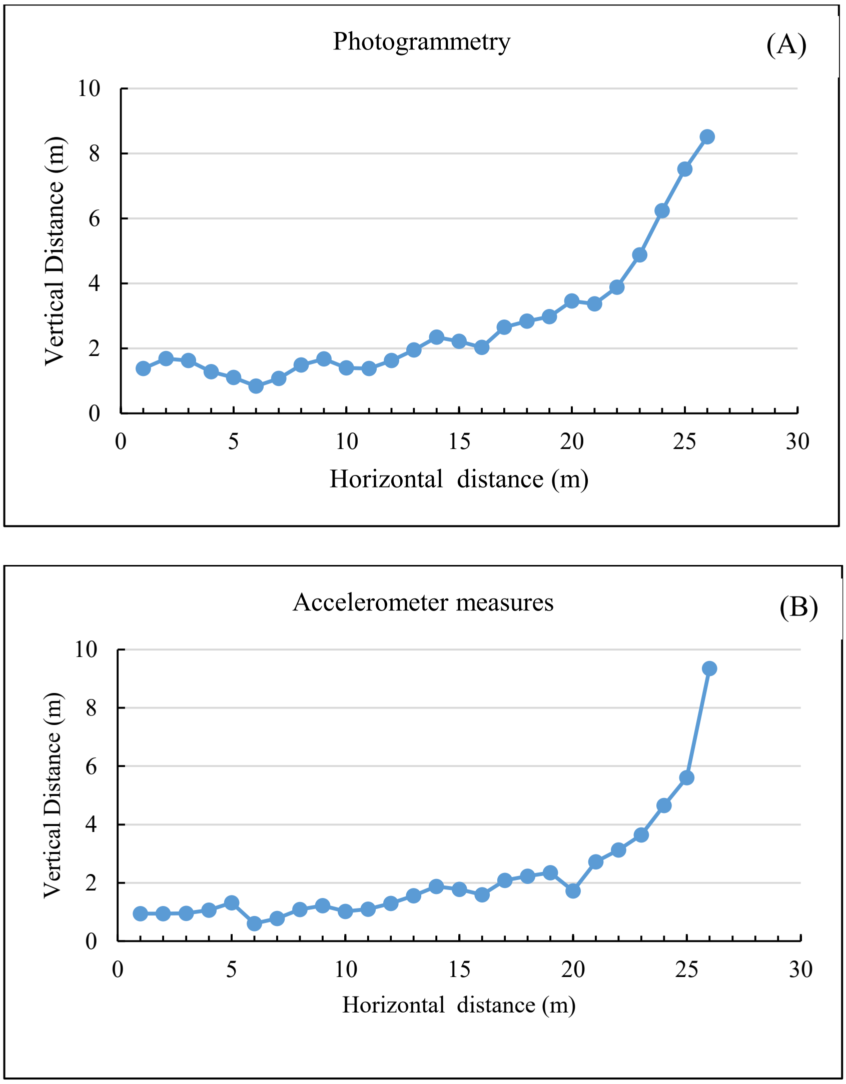


Figure 4.9: 25 frames of photogrammetry (A) and accelerometer measure (B) for sixth subject.

Table 4.6: Correlation between photogrammetry and accelerometer measure in load phases of gait for sixth subject

Variables	Photogrammetry technique(m)		Accelerometer measure(m)		R
	Mean	SD	Mean	SD	
Heel strike	1.41	0.21	0.26	0.13	0.93
Loading response	1.29	0.30	0.94	0.22	0.99
Midstance	1.90	0.36	1.52	0.29	0.99
Heel-off	2.79	0.47	2.00	0.29	0.79
Toe-off	4.50	1.20	3.95	1.05	0.99

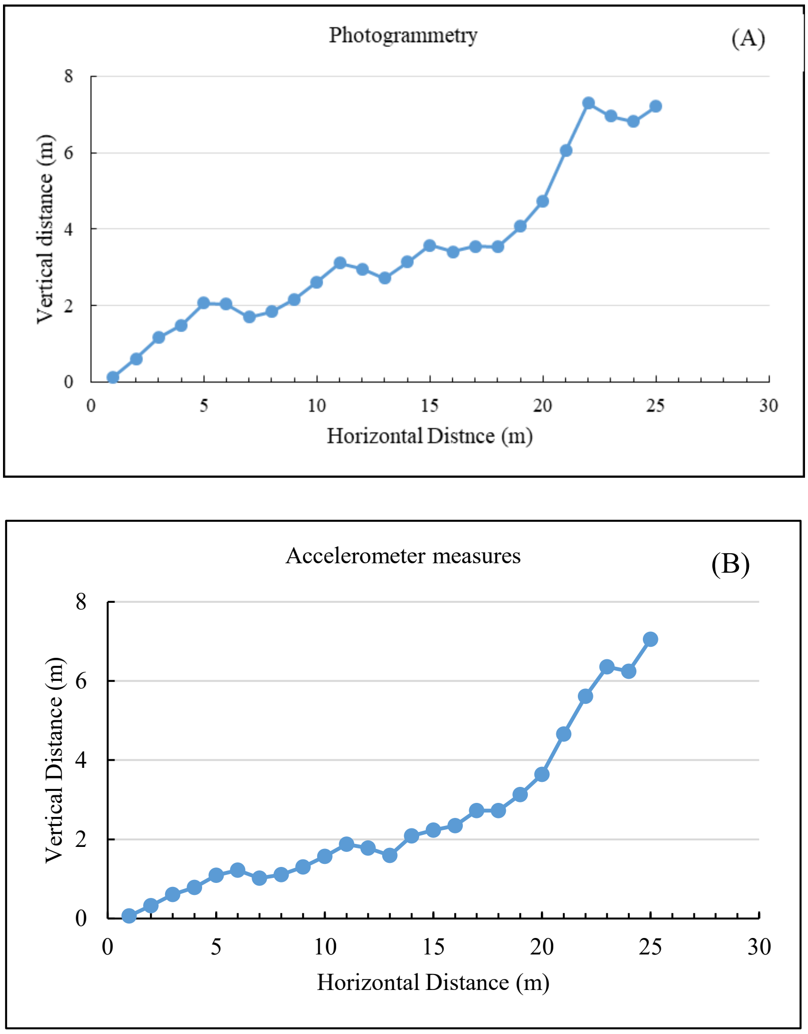


Figure 4.10: 25 frames of photogrammetry (A) and accelerometer measures (B) for seventh subject.

Table 4.7: Correlation between photogrammetry and accelerometer measures in load phases of gait for seventh subject

Variables	Photogrammetry technique(m)		Accelerometer measures(m)		R
	Mean	SD	Mean	SD	
Heel strike	1.09	0.67	0.57	0.36	0.98
Loading response	2.07	0.31	1.24	0.19	0.98
Midstance	3.17	0.37	1.91	0.23	0.97
Heel off	3.78	0.57	2.91	0.44	0.96
Toe off	6.87	0.44	5.98	0.81	0.93

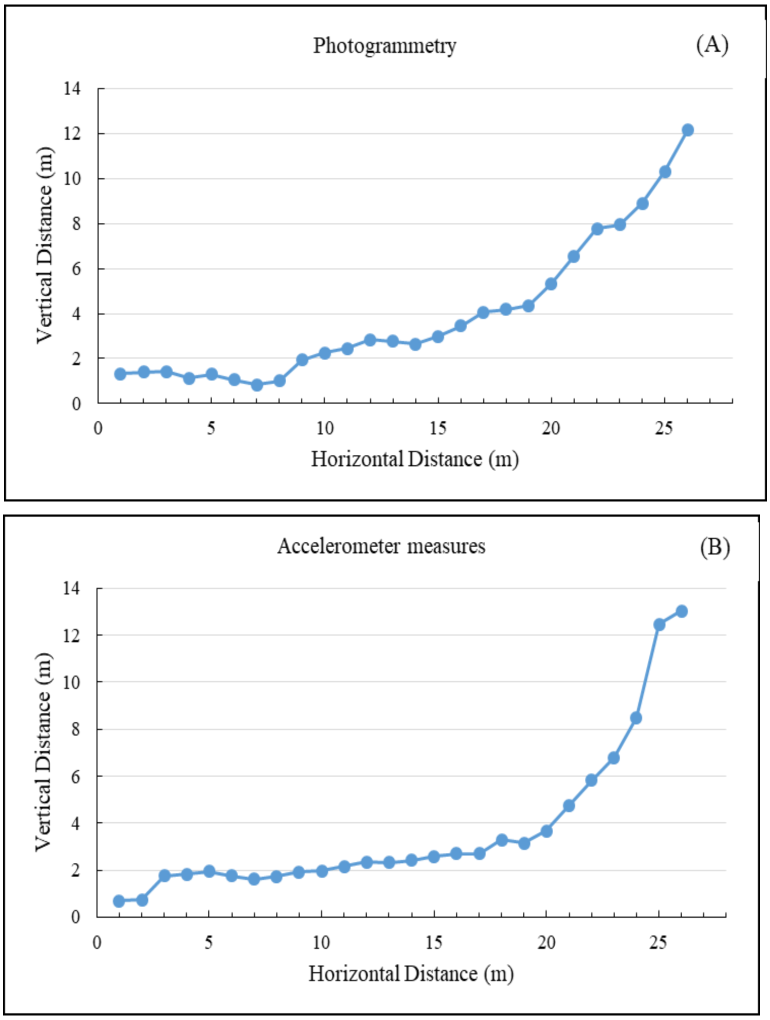
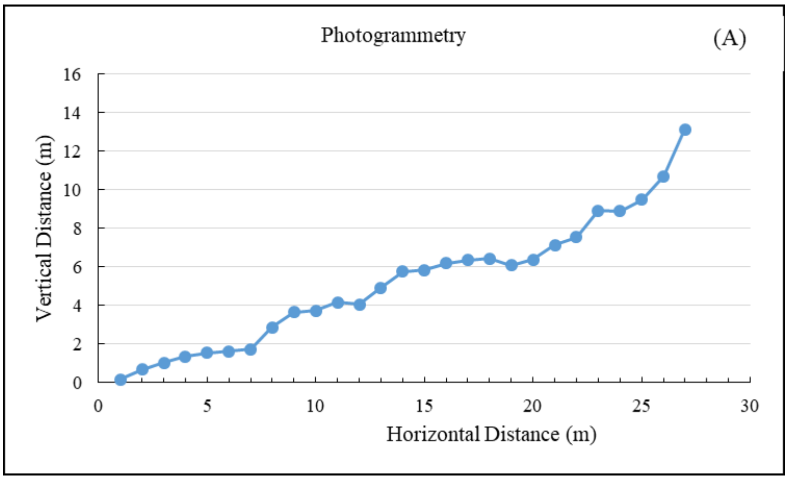


Figure 4.11: 25 frames of photogrammetry (A) and accelerometer measures (B) for eighth subject.

Table 4.8: Correlation between photogrammetry and Accelerometer measure in load phases of gait for eighth subject.

Variables	Photogrammetry technique(m)		Accelerometer measure(m)		R
	Mean	SD	Mean	SD	
Heel strike	1.32	0.10	0.78	0.08	0.68
Loading response	1.42	0.56	0.82	0.16	0.98
Midstance	2.74	0.18	1.37	0.14	0.67
Heel off	5.34	1.06	2.93	0.63	0.85
Toe off	8.98	0.73	8.26	3.80	0.99



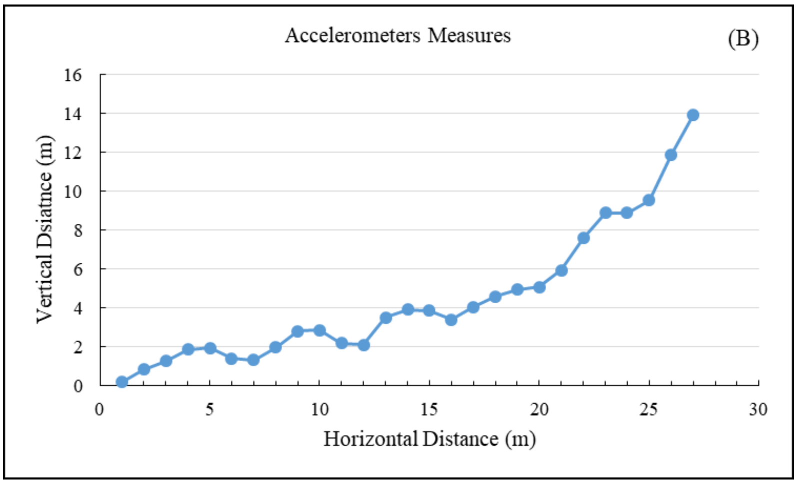
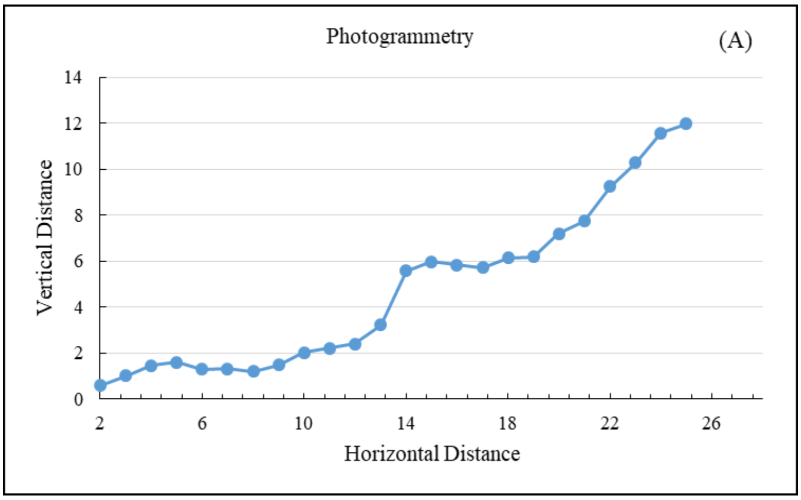


Figure 4.12: 25 frames of photogrammetry (A) and accelerometer measures (B) for ninth subject.

Table 4.9: Correlation between photogrammetry and Accelerometer measures in load phases of gait for ninth subject.

Variables	Photogrammetry technique(m)		Accelerometer measure(m)		R
	Mean	SD	Mean	SD	
Heel strike	0.96	0.49	1.26	0.69	0.98
Loading response	2.72	0.90	2.08	0.66	0.98
Midstance	4.95	0.75	3.33	1.06	0.95
Heel off	6.29	0.13	3.99	0.59	0.81
Toe off	8.40	0.89	8.17	1.28	0.99



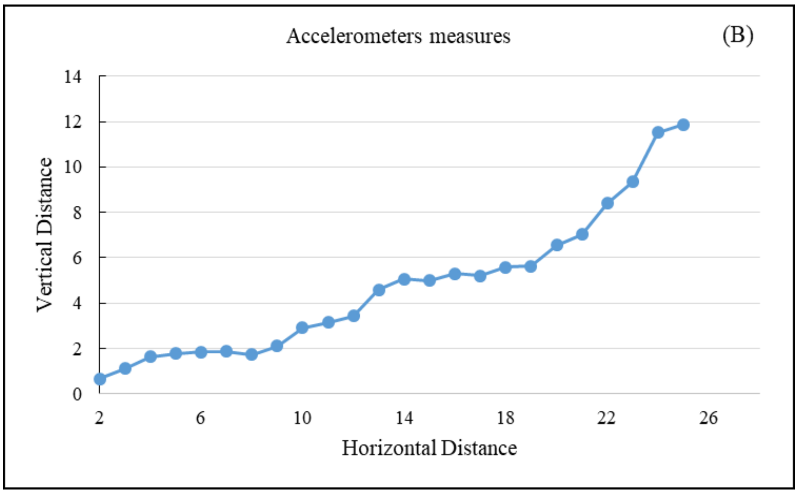


Figure 4.13: 25 frames of photogrammetry (A) and accelerometer measures (B) for tenth subject.

Table 4.10: Correlation between photogrammetry and Accelerometer measures in load phases of gait for tenth subject

Variables	Photogrammetry technique(m)		Accelerometer measure(m)		R
	Mean	SD	Mean	SD	
Heel strike	0.97	0.53	1.08	0.58	0.99
Loading response	1.47	0.30	2.09	0.42	0.99
Midstance	3.88	1.59	4.25	0.80	0.89
Heel off	6.22	0.52	5.65	0.47	0.98
Toe off	10.15	1.55	9.63	1.84	0.99

In summary, from the obtained results, we can notice that specific opportunities exist for smartphone-based gait assessment as an alternative to conventional gait assessment. Furthermore, a smartphone-based gait assessment could provide reliable information about changes in the spatiotemporal gait parameters.

4.3 Spatiotemporal gait parameters

In this part of our research, a number of experiments were conducted to evaluate the performance of the proposed method. Smartphone data based on accelerometer and F-scan were used in this study. As mentioned in Section 3.3.1, the purpose of the second part of the research methodology was to: Validate the smartphone sensor device by analysing spatiotemporal gait parameters. The quality of the new validated method can demonstrated by collecting spatiotemporal human gait parameter data for four devices (two smartphones and two insole sensors) with different groups using a cohort of 30 adults. Beside, determine the effectiveness of the characteristics of the gait parameters to identify and relationship between Smartphone and Insole sensors. In addition, we used different statistical method to evaluate the performance of the proposed method. The first test dataset was calculated from 10 subjects. The dataset for each subject was divided into three trials, and each participant walked 10m. The mean, standard deviation and interclass correlation coefficient measures were applied to evaluate the performance of the proposed method. These measures were computed for each subject and the average of the means, standard deviations and interclass correlation coefficients were calculated. Data were analysed with SPSS 23.0 (IBM Inc) and Excel 2013.

4.3.1 Performance quality of the developed method based on reliability and validity

During walking trials, the results showed values closer or similar to those recorded by the insole shoes and smartphone for all four parameters (step time, stride time, Candace and walking speed). Table 4.11 shows the average measure for all subjects. Reliability using the mean and SD was used to evaluate the proposed approach. These measures were recorded for using both insole and smartphone devices. Based on the obtained results presented in Table 4.11, we can see that the minimum SD was achieved when the smartphone device was used.

Table 4.11: Average of mean and SD for 10 subjects with four parameters.

Measures	Parameters															
	Step time (s)				Stride time(s)				Cadence(steps/min)				Walking speed (m/s)			
	Insole shoes		**Accelerometer measure**		**Insole shoes**		**Accelerometer measure**		**Insole shoes**		**Accelerometer measure**		**Insole shoes**		**Accelerometer measure**	
	L	R	L	R	L	R	L	R	L	R	L	R	L	R	L	R
Mean	**0.74**	**0.75**	**0.78**	**0.85**	**1.29**	**1.3**	**1.31**	**1.33**	**50.85**	**46.17**	**45.8**	**45.34**	**0.92**	**0.91**	**0.91**	**0.91**
SD	**0.02**	**0.03**	**0.06**	**0.05**	**0.05**	**0.05**	**0.04**	**0.07**	**2.74**	**1.76**	**1.46**	**2.38**	**0.04**	**0.03**	**0.04**	**0.03**

To investigate the effectiveness of the characteristics of the four factors of gait to identify the relationship between smartphone and insole shoes, the mean and SD measurements were used in this study, as shown in Figures 4.14, 4.15, 4.16 and 4.17. Figures 4.14 represented the mean and SD for the Insole sensor data for left step. Figure 4.15 represented the mean and SD for the accelerometer measure data for left step for 10 subjects. Figure 4:16 and 4:17 represented the Mean and standard deviation for four factors (right steps) for 10 subject for insole sensors data and accelerometer data respectively. From the obtained results, we can see that the four parameters (step time, stride time, cadence and walking speed) for left and right legs have reported a good results in term of SD. Based on the literature, the smartphone's obtained results indicate that the four parameters can be used to assess gait. The gait spatiotemporal parameters extracted from the smartphone device showed a good agreement compared to the insole shoes sensor.

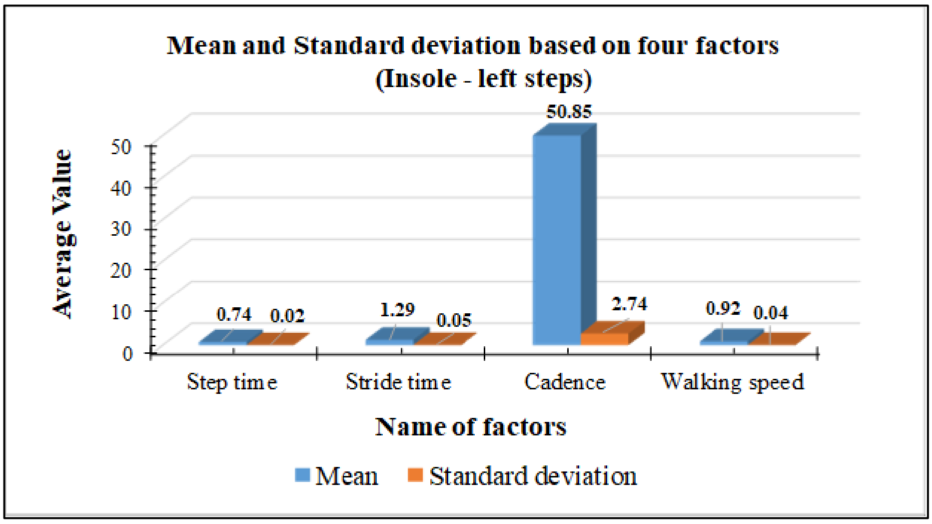


Figure 4.14: Mean and standard deviation for four factors insole sensors data (left step) for 10 subject.

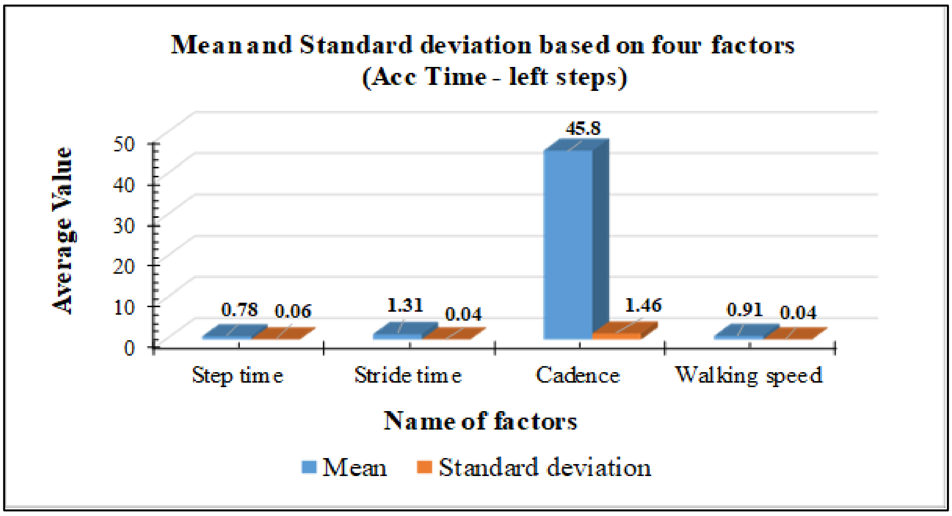


Figure 4.15: Mean and standard deviation for four factors accelerometer data (left steps) for 10 subject.

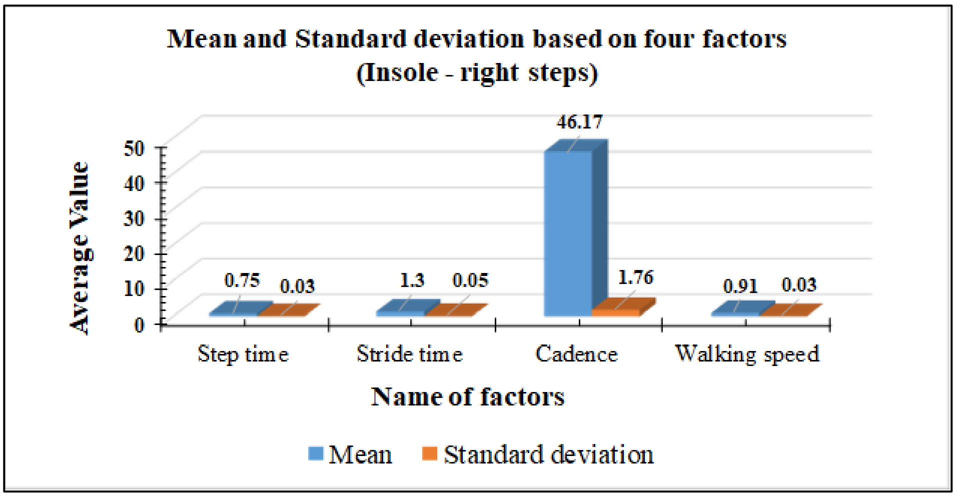


Figure 4.16: Mean and standard deviation for four factors insole sensors data (right steps) for 10 subject.

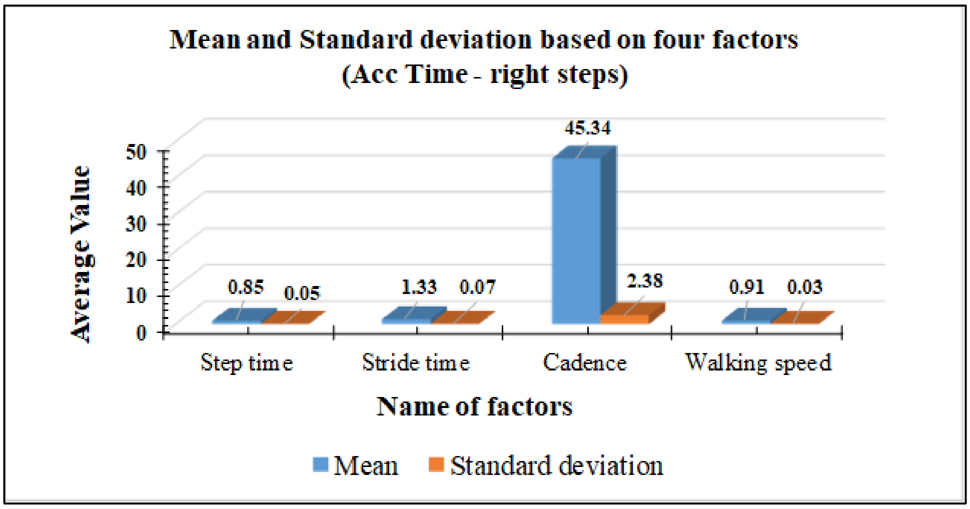


Figure 4.17: Mean and standard deviation for four factors accelerometer data (right steps) for 10 subject.

Regarding validity, the interclass correlation coefficient was employed in this study to evaluate the performance of the proposed method. Four spatio-temporal gait parameters of ten subjects were determined using two smartphones and two insole shoes.

Our findings show that there were some differences in the trials but they did not affect our results. The main reason for this is the gait time may vary for the same subject in each trial. In addition, the results of both devices (insole shoes and smartphones) show that the maximum time for the four parameters (step time, stride time, cadence and walking speed) of all subjects was 0.85s, 1.33s, 50.58 $_{min}$ and 0.92m/s respectively. These results demonstrate that the smartphone has the ability to record good reliability measures for gait assessment.

The interclass correlation coefficient (ICC) for the four parameters (step time, stride time, cadence and walking speed) was calculated. We used the following value to check agreement between the device results: .90 to 1.00 as very high, 0.70 to 0.90 as high, and 0.50 to 0.70 as moderate, 0.30 to 0.50 as low, and less than 0.30 as insignificant. These metrics and ranges of values were used by Mukaka (2012), Muheidat et al. (2017) and Howell et al. (2020).

The ICC was computed for 10 subjects, and the average for each subject was calculated. The ICC was used to evaluate the validity of the smartphone device. Tables 4.12, 4.13.4.14 and 4.15 show the ICC results using the four parameters. The ICC showed closer readings between the smartphones and insole shoes.

The step time, stride time, cadence and walking speed achieved excellent to fair results of ICC among all the subjects with an average ICC 41-96. Based on the literature, the ICC in this study is acceptable.

Finally, the proposed approach using smartphone and insole achieves the best performance in terms of the mean, SD and ICC. This smartphone method can help researchers in recording gait characteristics such as step time, stride time, cadence and walking speed with accurate and reliable results, and it potentially reduces the costs of obtaining data.

Table 4.12: Differences in step time for each individual (number of trials=3)

	Left step (L)			Right step (R)		
Subjects ID	**Insole**	**Accelerometer Measures**		**Insole**	**Accelerometer Measures**	
	Mean(s)± SD(s)	Mean(s)± SD(s)	ICC	Mean(s)± SD(s)	Mean(s)± SD(s)	ICC
ID1	0.74±0.02	0.78±0.06	0.75	0.74±0.03	0.85±0.05	0.88
ID2	0.74±0.02	0.81±0.05	0.71	0.77±0.04	0.8±0.04	0.71
ID3	0.71±0.11	0.69±0.08	0.96	0.73±0.11	0.85±0.11	0.93
ID4	0.737±0.017	0.77±0.02	0.93	0.72±0.02	0.74±0.01	0.75
ID5	0.69±0.02	0.68± 0.02	0.70	0.67±0.02	0.68±0.02	0.76
ID6	0.7±0.01	0.72±0.02	0.41	0.72±0.01	0.85±0.05	0.55
ID7	0.71±0.01	0.78±0.02	0.76	0.75±0.01	0.78±0.01	0.85
ID8	0.75±0.06	0.73±0.05	0.98	0.77±0.06	0.81±0.09	0.93
ID9	0.72±0.02	0.74±0.01	0.81	0.72±0.02	0.74±0.01	0.75
ID10	0.68±0.03	0.69±0.04	0.96	0.7±0.02	0.7±0.01	0.81

Table 4.13: Differences in stride time for each individual (number of trials =3)

Subjects ID	Left step (L)			Right step (R)		
	Insole	Accelerometer Measures		Insole	Accelerometer Measures	
	Mean(s)± SD(s)	Mean(s)± SD(s)	ICC	Mean(s)± SD(s)	Mean(s)± SD(s)	ICC
ID1	1.29±0.05	1.31±0.04	0.88	1.30±0.05	1.33±0.07	0.87
ID2	1.29±0.01	1.29±0.01	0.85	131.±0.01	1.28±0.02	0.88
ID3	1.31±0.19	1.25±0.22	0.96	1.31±0.2	1.3±0.18	0.98
ID4	1.26±0.03	1.27±0.05	0.91	1.28±0.03	1.28±0.03	0.94
ID5	1.25±0.05	1.27±0.03	0.95	1.24±0.04	1.23±0.04	0.98
ID6	1.3±0.01	1.31±0.04	0.63	1.29±0.04	1.33±0.07	0.70
ID7	1.3±0.02	1.29±0.01	0.77	1.3±0.001	1.29±0.01	0.88
ID8	1.31±0.19	1.25±0.22	0.96	1.31±0.02	1.3±0.08	0.91
ID9	1.29±0.008	1.3±0.03	0.81	1.29±0.02	1.31±0.03	0.97
ID10	1.26±0.05	1.27±0.03	0.95	1.26±0.04	1.24±0.03	0.95

Table 4.14: Differences in Cadence for each individual (number of trials =3)

Subjects ID	Left step (L) Insole mean± SD (steps/min)	Left step (L) Accelerometer Measures mean± SD (steps/min)	Left step (L) ICC	Right step (R) Insole mean± SD (steps/min)	Right step (R) Accelerometer Measures mean± SD (steps/min)	Right step (R) ICC
ID1	50.85±2.27	45.82±1.46	0.79	46.17±1.76	45.34±2.38	0.72
ID2	46.58±0.6	46.37±0.49	0.78	45.76±0.29	46.06±0.29	0.63
ID3	46.69±6.93	49.65±8.12	0.94	46.85±7.24	46.84±6.88	0.98
ID4	47.56±1.184	47.19±1.92	0.93	46.74±1.12	46.86±1.12	0.96
ID5	47.6±1.91	47.31±1.22	0.94	48.17±1.5	48.64±1.36	0.96
ID6	50.07±2.83	46.89±0.56	0.53	45.30±1.6	45.68±1.84	0.61
ID7	45.25±0.25	46.37±0.49	0.85	45.43±0.72	45.75±0.45	0.89
ID8	47.38±6.16	50.77±6.56	0.93	47.6±6.43	47.61±6.11	0.94
ID9	48.24±0.3	47.75±1.22	0.61	47.37±0.35	47.01±0.91	0.68
ID10	48.10±1.57	47.31±1.22	0.97	48.39±0.79	48.3±0.89	0.89

Table 4.15: Differences in walking speed for each individual (number of trials =3)

Subjects ID	Left step (L) Insole Mean(m/s)± SD(m/s)	Left step (L) Accelerometer Measures mean(m/s) ± SD(m/s)	ICC	Right step (R) Insole mean(m/s)± SD(m/s)	Right step (R) Accelerometer Measures mean(m/s)± SD(m/s)	ICC
ID1	0.90±0.02	0.90±0.01	0.63	0.91±0.02	0.91±0.02	0.69
ID2	0.90±0.01	0.89±0.02	0.93	0.88±0.02	0.88±0.01	0.85
ID3	1.00±0.22	0.98±0.16	0.97	0.93±0.12	0.87±0.10	0.80
ID4	0.90±1.00	0.90±0.03	0.70	0.90±0.01	0.91±0.01	0.82
ID5	0.92±0.03	0.93±0.05	0.83	0.90±0.03	0.93±0.01	0.76
ID6	0.92±0.01	0.9±0.01	0.79	0.93±0.01	0.92±0.02	0.90
ID7	0.92±0.02	0.88±0.01	0.71	0.88±0.02	0.89±0.01	0.82
ID8	0.88±0.05	0.90±0.06	0.83	0.88±0.04	0.91±0.05	0.88
ID9	0.90±0.01	0.89±0.01	0.80	0.92±0.01	0.90±0.01	0.98
ID10	0.95±0.02	0.95±0.01	0.97	0.96±0.01	0.95±0.04	0.90

The smartphones and insole shoes show agreement and offer high performance quality results. This scheme was implemented and tested on a benchmark database which used only ten subjects with three trials. According to the results in (Mnati & Chong 2020), a smartphone versus insole shoe technique yielded promising results with high agreement. To improve the our results and make it more reliable we increased the number of subjects and trials, based on smartphone and insole sensors, was presented in this chapter; it was conducted and tested with a whole database, 20 subjects 10 men and 10 women; aged 20 and 40 years; mass and height 60 to 95 kg and 156 to 180cm, respectively), using five trials.

The second phase of results were discussed the smartphones vs insole shoe technique of a whole dataset, with 20 subjects. This method improved performance by increasing the performance results using new statistic measures with a whole dataset.

The results of each subject lower limb were reported in terms of mean and SD, as shown in Tables 4.15 and 4.16. Where, the results of 20 subjects left and right legs are described in details in Appendix C2. These statistical measures are used by many researchers to evaluate their research methods (Silsupado et al., 2020; Hollman et al., 2016). The results of all experiments were analysed using SPSS 23.0. Tables 4.15 and 4.16 show the average (for 20 subjects) of four parameters for left and right insole sensor and smartphone, based on mean and SD.

Table 4.16: Performance of proposed method based on four parameters - left insole sensor and smartphone for five trials m/s

Variable	Insole		Smartphone	
	Mean	**SD**	**Mean**	**SD**
Step time(s)	0.68	0.03	0.67	0.03
Stride time(s)	1.22	0.06	1.22	0.06
Cadence(steps/min)	50.05	0.92	49.35	1.03
Walking time(m/s)	1.03	0.05	1.02	0.05

Table 4.17: Performance of the proposed method based on four parameters – right insole sensor and smartphone for five trials

Variable	Insole		Smartphone	
	Mean	**SD**	**Mean**	**SD**
Step time(s)	0.68	0.02	0.69	0.03
Stride time(s)	1.21	0.05	1.21	0.05
Cadence(steps/min)	49.81	0.78	49.41	0.96
Walking speed (m/s)	1.01	0.05	1.01	0.05

The mean and SD for each subject based on the four parameters were computed. The average was calculated for each parameter for both insole sensors and smartphones. Based on the results in Tables 4.16 and 4.17, the mean and SD for insole and smartphone based on the three parameters yielded approximately the same results except cadence. The results demonstrated that the smartphone has the ability to measure the spatiotemporal parameters of healthy people.

Two of the twenty subjects participating in this study were randomly selected to perform 25 trials. This procedure was performed to collect more data, leading to a better understanding of the proposed study in terms of the comparison between smartphones and insole sensors. In other words, the more trials have taken, the closer average will get to the true value. The results for each subject is based on four parameters (step time, stride time, cadence and walking speed), and are reported in terms of mean ± SD, and then the average of mean ± SD was calculated for all subjects, as shown in Table 4.16. The results for the smartphone measure demonstrate that the developed study achieved a perfect results when comparing smartphone and insole sensors. Of the four parameters, the step time results performed best in terms of average of mean and SD for all subject compared with other parameters. In the Table 4.17, it could be seen that the smartphone pair achieved a good results compared with that of the insoles in the four parameters (step time, stride time, Cadence and walking speed.

Table 4.18: Results for mean ± SD for 25 trials

Parameters	Insole		Smartphone	
	Right	Left	Right	Left
	mean ± SD	mean ± SD	mean ± SD	mean ± SD
Step time(s)	0.76 ± 0.03	0.74 ± 0.03	0.78 ± 0.03	0.73 ± 0.03
Stride time(s)	1.30 ± 0.05	1.31 ± 0.05	1.27 ± 0.24	1.31 ± 0.05
Cadence(steps/min)	45.41 ± 1.75	45.78 ± 1.62	45.75 ± 1.60	45.73 ± 1.74
Walking time(m/s)	0.92 ± 0.09	0.89 ± 0.08	0.90 ± 0.06	0.89 ± 0.07

The P-value was used to determine significance by presenting the agreement between the smartphones and insoles. The differences between the data derived from the insole sensor and smartphone were (P-value >0.05), reflecting the similarity between these two devices, as shown in Table 4.18. Results confirm the hypotheses formulated prior to this study and therefore are supportive of the increased adoption of smartphones for collecting spatiotemporal data instead of insole sensors.

Table 4.17 shows the summary of results based on the Pearson correlation coefficient (r) and P-value between smartphones and insole sensors for all subjects in 25 trials. Analysis used the range of (r) values 0.90-1.00 considered very high, 0.70-0.90 high, 0.50-0.70 moderate, 0.30-0.50 low and less than 0.30 negligible (Silsupadol et al. 2019). The P-value was calculated for all parameters through insole and smartphone (left and right). The results in Table 4.18 show that each parameter for insole and smartphone could be statistically evaluated by a specific set of P-values.

Table 4.19: Summary of results agreement between accelerometer measures and insoles for two subjects with 25 trials

Variable	Right		Left	
	Pearson r	*P*-value	Pearson r	*P*-value
Step time(s)	0.79	0.42	0.79	0.26
Stride time(s)	0.92	0.31	0.88	0.08
Cadence(steps/min)	0.80	0.47	0.88	0.08
Walking time(m/s)	0.82	0.46	0.80	0.94

4.3.2 Performance of the study based on Bland Altman plots

Bland Altman plots were used to assess this study's ability to investigate the effectiveness of the variables (step time, stride time, cadence, and walking speed). Bland Altman plots are another way to examine the agreement and systematic error between the smartphones and insoles (Howell et al. 2020). The x-axis represents the average of the two systems' values while the y-axis represents the difference between the two values. The Bland Altman graph has three horizontal lines that provide more information about the acquired data. The solid line, called the bias, represents the average differences between the two values, and the two dashed lines represent the limit of agreement (LOA). Bland Altman plots show bias and 95% limits of agreement when comparing the spatiotemporal gait parameters derived from the smartphones and insole sensors, as shown in Figure 4.18. If 95% of the values fall between the dashed lines, the difference is normally distributed (Myles & Cui 2007). Based on the obtained results in Figure 4.18, we can observe that there are no big differences in the obtained results when the smartphones and insole sensors were used, indicating that there is an agreement between both devices. From these results, it is evident that the smartphone has the ability to determine spatiotemporal gait parameters, and to evaluate the validity of a smartphone-based tri-axial accelerometer to assess gait characteristics.

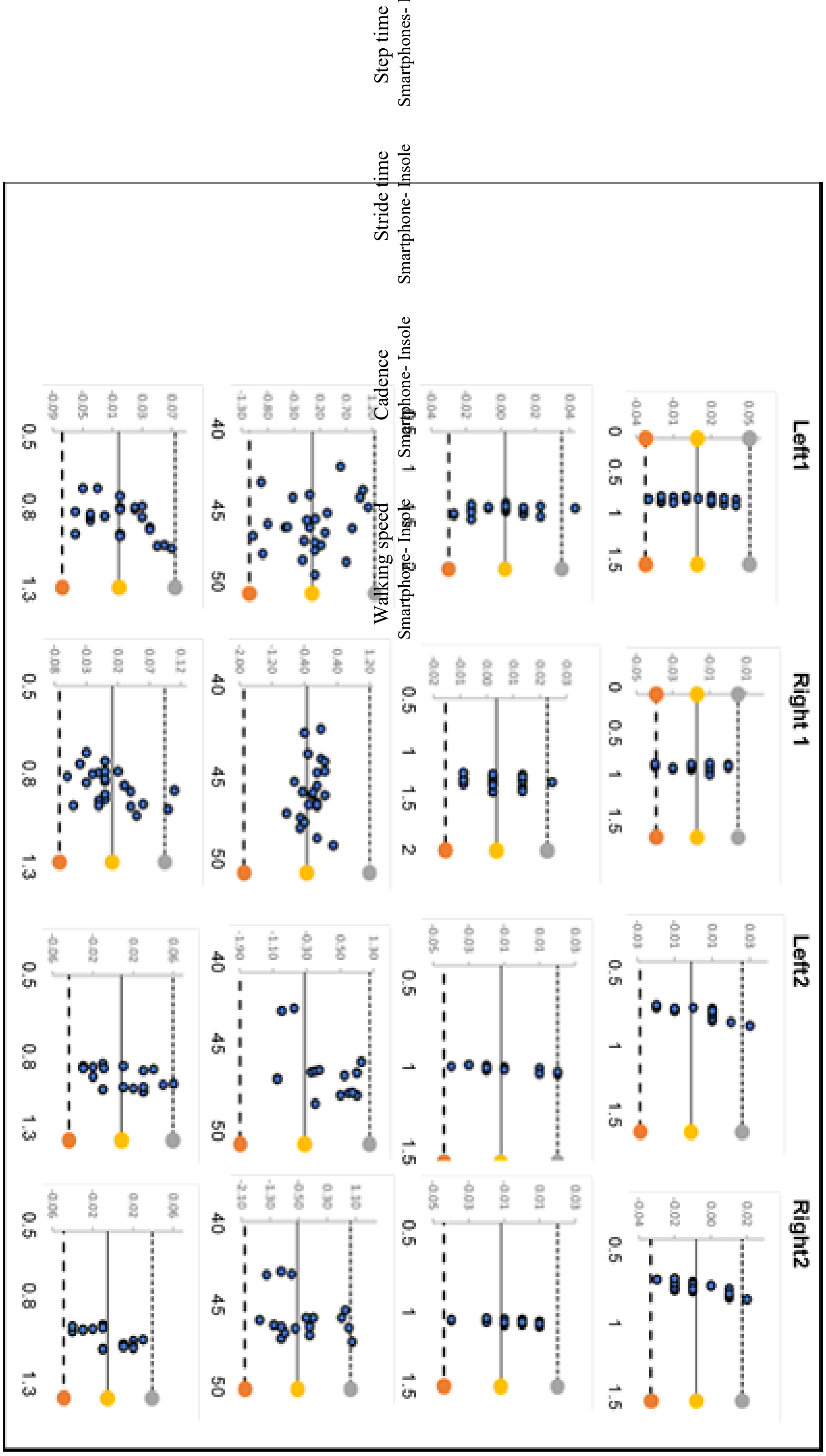


Figure 4.18: Bland-Altman plot for Samsung smartphone attached to subject's body and insole sensors for two subjects with 25 trials. Each dot represents a single step. The solid line is the bias, with dashed lines representing the upper and lower of error LOA.

4.3.3 Performance of the developed study based on 25-cross validation

To investigate the effectiveness of the smartphones as opposed to the insole sensors in determining spatiotemporal gait parameters (step time, stride time, cadence and walking speed), box plots were used based on the Pearson correlation coefficient. The box plots consist of three parts: upper, lower, and middle. The upper part of the plot box denotes the 75th percentile, and the lower part presents the 25th percentile, while the central part refers to the median 50th percentile which is sometimes called the centre. The highest and lowest values in the box plot are marked using a line extending from the top to the bottom of the box. The box plot shows agreement between smartphones and insole sensors at the same time point based on the Pearson correlation coefficient. In further investigations, the performance of the proposed method through 25-cross validation using the smartphone was used in this study. The proposed method was tested 25 times, and all results were recorded. From Figures 4.19 A and B we can see that the Pearson correlation coefficient ranged between 0.79 and 0.92 for both the left and right. In Figure 4.19A, the value of the maximum Pearson correlation coefficient was 0.98% for stride time left, while the minimum value was 0.68% for walking speed left. On the other hand, the maximum and minimum Pearson correlation coefficient for the right limb was 0.98% and 0.65% for stride time and step time, respectively.

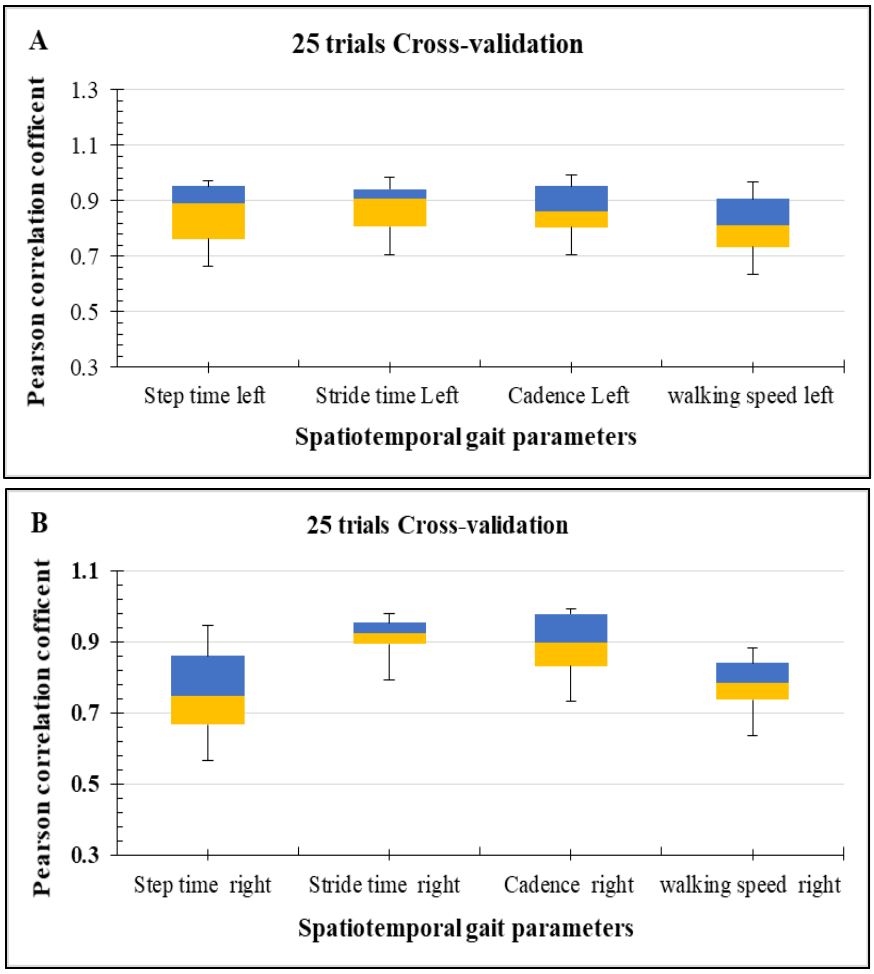


Figure 4.19: Box plot for Pearson correlation coefficient of smartphones and insole sensors: A shows the left leg and B shows the right leg.

For further evaluation of the study, the performance of the smartphones and insole sensors were analysed and tested for spatiotemporal gait parameters using R-squared (R^2). The scatterplot of the insole sensor versus smartphone device with the least square regression, line and correlation of determination (R^2) which is used to evaluate as well as to show the agreement between smartphones and insole sensors for all gait parameters. The constant values of a and y-intercept b were used to outline the model's performance, with the correlation of determination (R^2), was employed. Reliable results were found for all four parameters: step time, stride time, cadence and walking, based on the value a, b and R^2. Furthermore, it was noticed that there is agreement between the smartphones and insole sensors, which reported the same or similar results. The results for the left leg were $R^{2=}$ 0.81, 0.88, 0.8 and 0.80 for step time, stride time, cadence and walking, respectively, while results for the right leg were $R^{2=}$ 0.85, 0.96, 0.87 and 0.81 for step time, stride time, cadence and walking, respectively.

Figures 4.20, 4.21, 4.22 and 4.23 represent four parameters of left and right legs of the first subject. Step time shows high agreement for left and right legs with $R^2 > 0.80$ Figure 4.20. Figure 4.21 shows less agreement in the left leg $R^2 = 0.88$ compare to the right leg $R^2 = 0.96$ in stride time. For Cadence $R^2 = 0.87$ for both left and right legs as shown in Figure 4.22. Also, the results were slightly different in the walking speed parameter $R^2 = 0.80$ for left and $R^2 = 0.81$ for the right leg. Furthermore, for subjects 2 with 25 trials, R^2 for left and right legs was 0.83 and 0.84 respectively as shown in Figure 4.24. Figure 4.25 shows that less agreement between insole and smartphone measures in stride time, $R^2 = 0.75$ for left and $R^2 = 0.83$. In Cadence, both left and right legs $R^2 = 0.77$ and $R^2 = 0.70$ as shown in Figure 4.26. Figure 4.27 shows that right leg data in walking speed has higher agreement than the left leg.

Finally, the experimental outcomes indicate that the developed method can measure the spatiotemporal parameters of healthy people: step time, stride time, cadence and walking speed, using both insole sensors and smartphones.

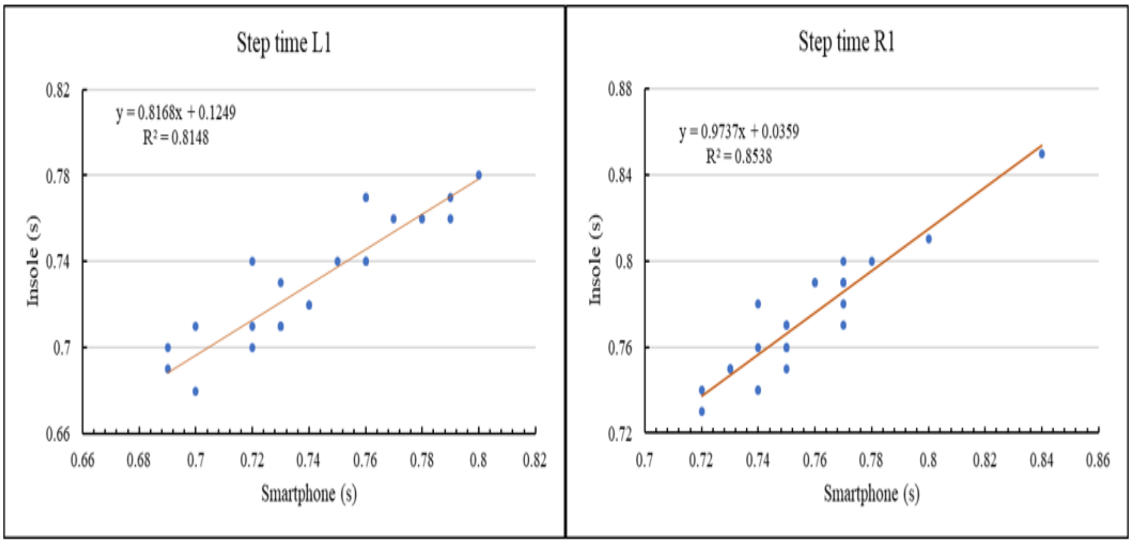


Figure 4.20: Scatterplot of smartphone device versus insole sensor for left and right legs' step time for first subject.

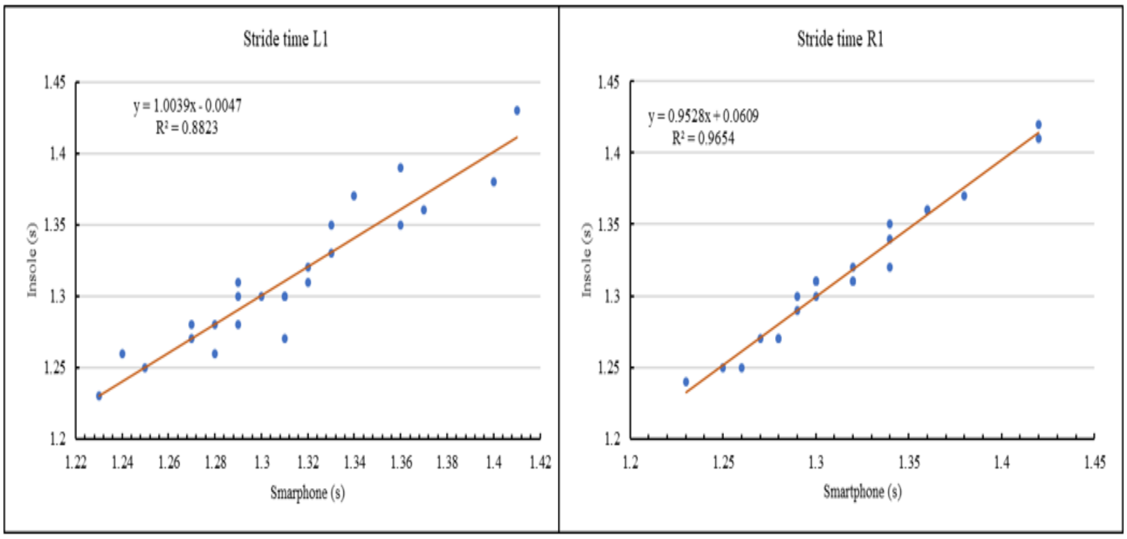


Figure 4.21: Scatterplot of smartphone device vs insole sensor for left and right legs' stride time for first subject

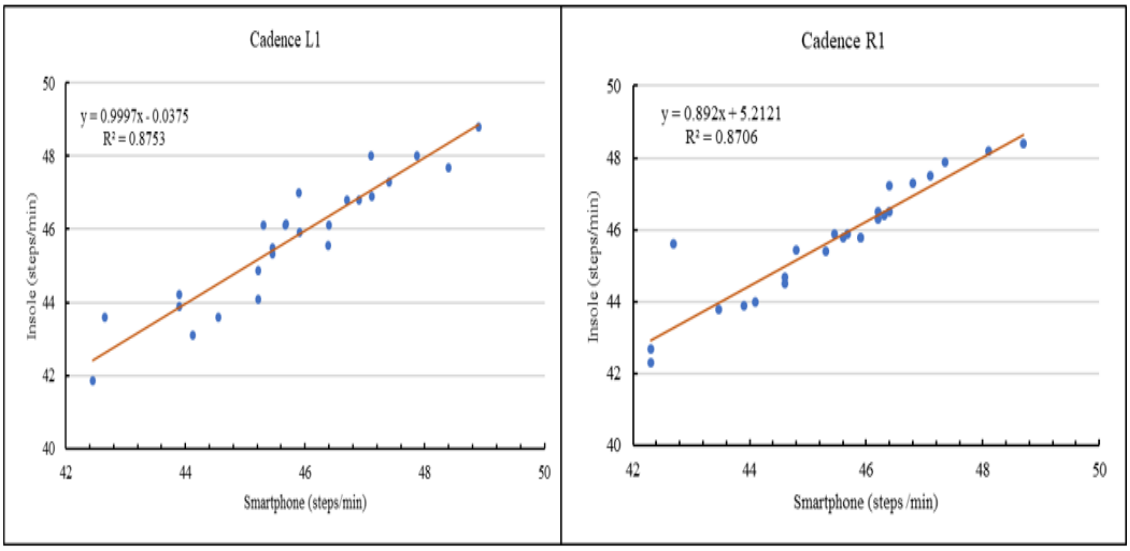


Figure 4.22: Scatterplot of smartphone device versus insole sensor for left and right legs' cadence for first subject.

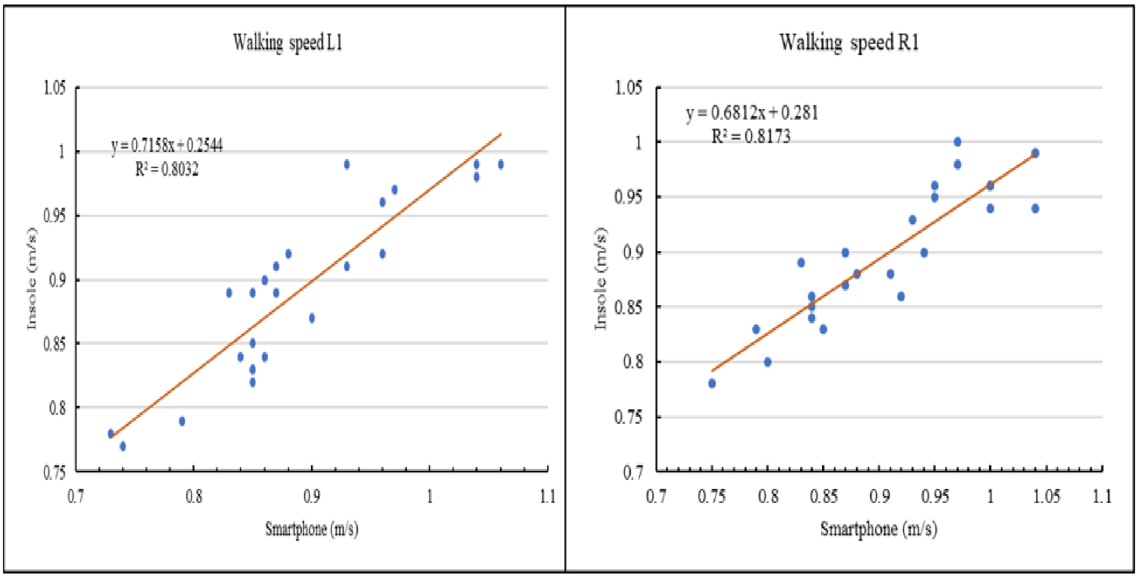


Figure 4.23: Scatterplot of smartphone device versus insole sensor for left and right legs' walking speed for first subject.

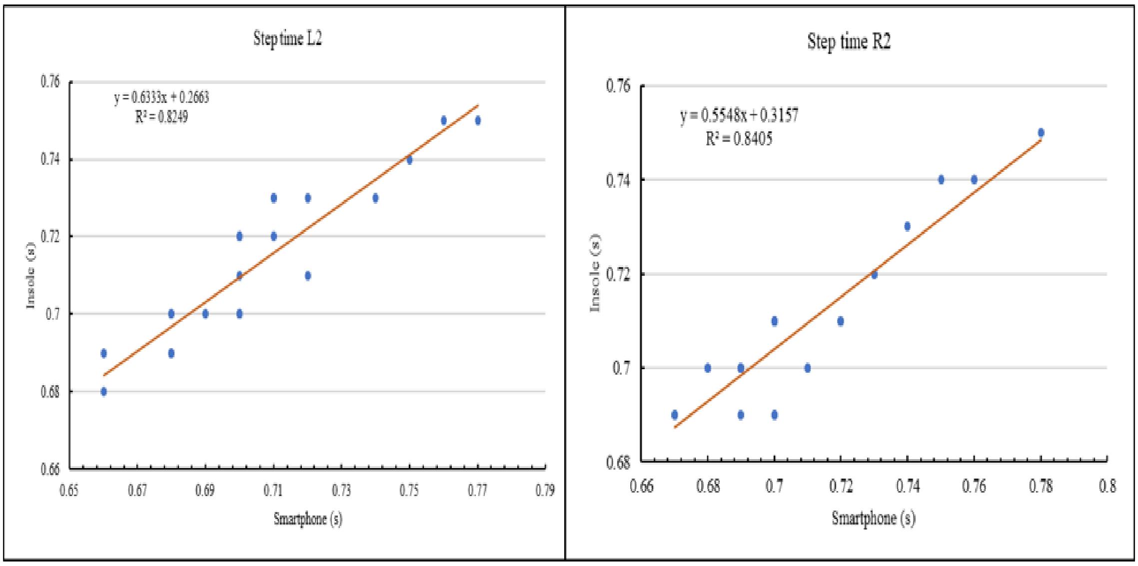


Figure 4.24: Scatterplot of smartphone device versus insole sensor for left and right legs' step time for second subject.

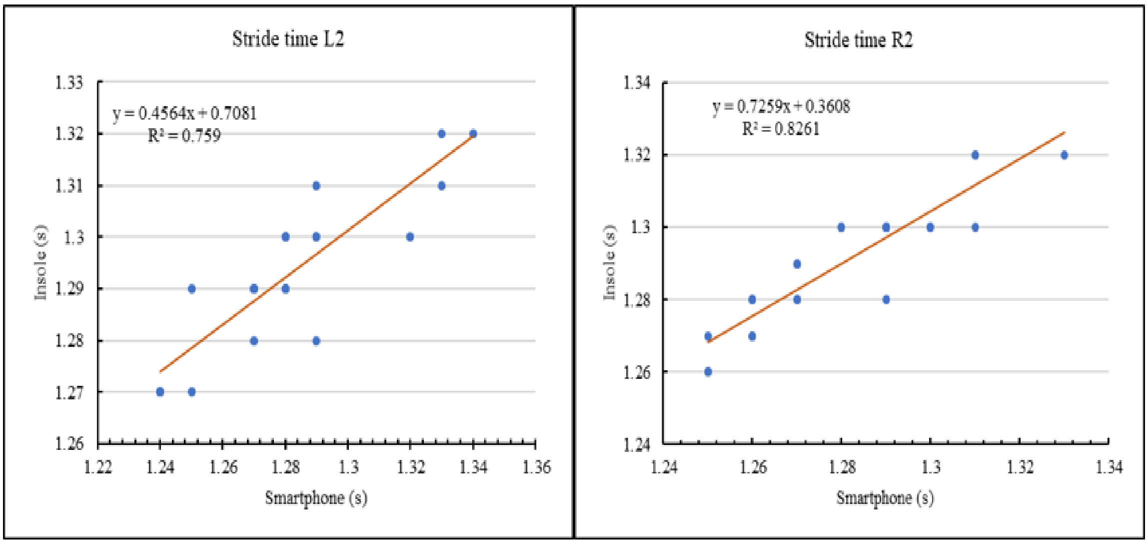


Figure 4.25: Scatterplot of smartphone device versus insole sensor for left and right legs' step time for second subject.

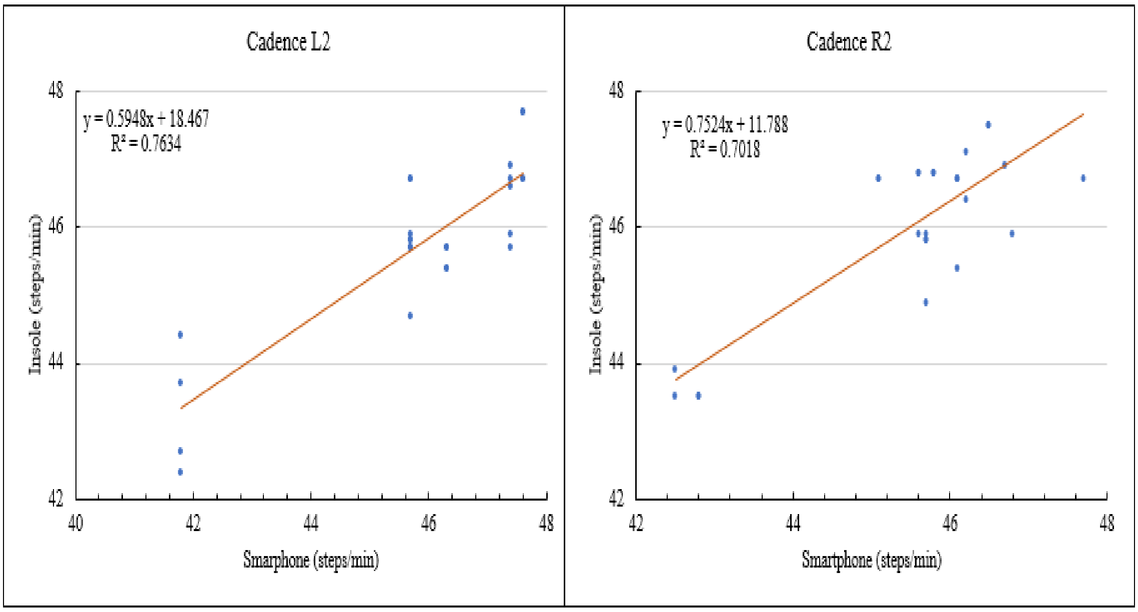


Figure 4.26: Scatterplot of smartphone device versus insole sensor for left and right legs' cadence for second subjects.

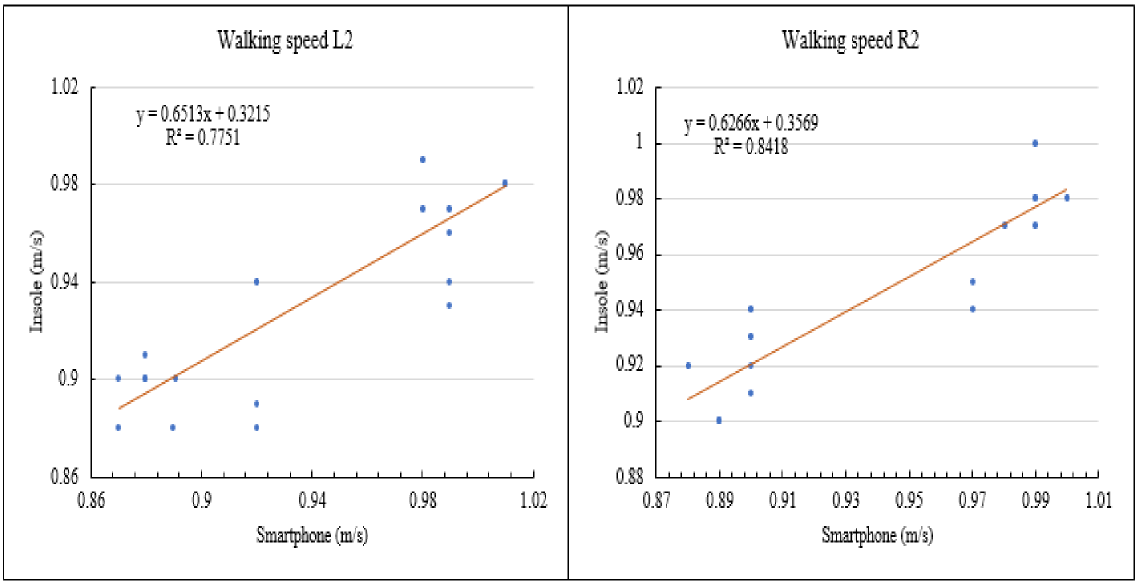


Figure 4.27: Scatterplot of smartphone device versus insole sensor for left and right legs' walking time for second subject.

4.4 Summary

This chapter has addressed the results of the research objectives. The results are divided into two parts: kinematic (accelerometer with photogrammetry) and spatiotemporal (accelerometer with insole sensors) results. The obtained results support our hypothesis that smartphone devices can provide close readings and gait measurements in comparison to the camera by taking the accelerometer reading as a parameter to compare the location of the limb during the stance phase of the gait. Also, the second part of the results demonstrate that the accelerometer sensor is efficient in its measurement of the spatiotemporal gait parameters of healthy adult participants. Thus, it can provide reliable data; negating the need for expensive devices.

CHAPTER 5: DISCUSSION

5.1 An Overview

This chapter discusses and evaluates the efficiency of the developed method. This research aimed to investigate the gap in chapter one. So, the first part of this research is focused on determining the existing accelerometer measures obtainable with smartphone devices, and investigating the smartphone device application and sensors to understand how they can be used in gait analysis research. It also introduces a new technique of smartphone sensor devices by comparing the captured data with camera images based photogrammetric data. The first part of the thesis is achieved the first objective in this research.

The second part of this research seeks to validate the smartphone sensor device by analysing spatiotemporal gait parameters. The quality of the new method examined the efficacy of accelerometer sensors in a pair of Android smartphones (one for each leg) as opposed to an insole sensor in determining spatiotemporal gait parameters. Also, investigated the effectiveness of gait parameters characteristics to identify the relationship between smartphone and insole sensors. The spatiotemporal gait parameters of 30 healthy participants in different cohort were assessed with insole sensors and smartphones.

Various studies have defined methods to assess body and leg movement via photogrammetry or accelerometers sensors. Photogrammetry has gained popularity in kinematic gait analyses such as those of ankle movement (Al-Kharaz & Chong 2020). This study determines the gender differences in ankle mobility. Twenty participants (10 females and 10 males) were recruited, and 14 retro-reflective targets were mounted on the skin of each participant's right foot. The results show that the sagittal range of motion in the plantar flexion turn in place is significant. The maximum mean angle of internal/external ankle rotation for males and females is very similar (there is no significant difference). These results may contribute to a better understanding of the influence of gender on ankle mobility.

Another study was presented by Yuan et al. (2002) in which a real-time photogrammetric system that incorporated multithreading and a graphic processing unit (GPU) provided an accelerated solution for extracting 3D human body dynamics in real-time. The system includes a stereo camera with preliminary calibration, from which left-view and right-view frames are loaded. Then, a dense image-matching algorithm is married with GPU acceleration to generate a real-time disparity map which is further extended to a 3D map array obtained by photogrammetric processing based on the camera orientation parameters. These 3D features are extracted and visualised in real-time by multithreading, from which human movement dynamics (e.g., moving speed, knee pressure angle) are derived. The results reveal that a real-time photogrammetric system is an effective real-time solution to monitor 3D human body dynamics. This proposed system has great potential for applications such as motion tracking, 3D body information extraction and human dynamics monitoring.

Furrer et al. (2015) proposed the different assessed method by smartphone application and motion capture system. a smartphone device used to compare the motion capture systems. In their study, 22 healthy young adults were assessed with a smartphone application and a motion capture system. The reliability of their proposed method was evaluated using the correlation coefficient and standard error. They demonstrated that there was agreement in the obtained results of the systems.

Another study was presented by (Phoophuangpairoj 2016) which analysed knee extension exercises using a smartphone accelerometer. This research developed a method to analyse a knee extension exercise using an accelerometer. The important factors affecting the effectiveness of the exercise to relieve knee pain were recognized. Regression analysis was applied to obtain a suitable equation to compute the knee angle from accelerometer data. Then, by applying signal processing, all knee angles were divided into small frames and used to identify the characteristics of the knee extension exercises. The results showed that the proposed method could efficiently determine the degree at which the leg was held, the length of time for which the leg was held, and the angular velocity at which the leg was lowered and raised. No research has focused on integrating two approaches such as photogrammetry and accelerometer for the purpose of gait analysis.

5.2 Smartphone versus photogrammetry measure accuracy

To our knowledge, this is the first study to compare and validate the use of smartphones versus cameras. Our hypothesis assumed that smartphone devices could provide close readings and gait measurements comparable to the camera by taking the accelerometer reading as a parameter to compare the location of the limb during the stance phase of the gait.

The results revealed some outstanding findings regarding smartphone use as a gait measurement device during human walking and running. It is worth noting that the linear location values for the whole stance phase are relatively similar and closer to that of a camera's 3D location in the x y planes (Z direction) which represents the linear location of the knee. Importantly, the correlation coefficient between the measurement of smartphone and camera was R= 0.935. Also, the relationship between the smartphone and camera is positive (R =0.87) which supports the hypothesis that the smartphone can be utilised as tool for the measurement of gait characteristics. During the toe-off segment of gait, the results showed a P value 0.56, giving an indication that this technique can produce similar values to that of a photogrammetry in some phases of the gait. There are some limitations in this research such as the small number of participants and the number of trials performed. Thus, further studies are required employing different types of smartphone devices, recruiting more subjects, and studying different gait parameters.

5.3 Smartphone versus insole sensors measure accuracy

In this part of our research, a new method was presented to study the four gait spatiotemporal parameters of healthy adult participants. This research developed an innovative method to extract the most important features from 10 subjects. The results showed the efficiency of the alternative devices in detecting the gait parameters of healthy adult participants; reporting close or similar results. Smartphone sensors can provide reliable data, inexpensively.

In this work, an innovative method was used to extract the most important features from 20 subjects. One of the most important findings was that the measures of the smartphone device agree with the insole shoe sensors when measuring spatiotemporal parameters. The effectiveness of the proposed model was tested with two Android smartphones, two insole sensors and 20 healthy adult participants. The study used different statistical methods (ANOVA, Bland-Altman, linear regression, and Pearson correlation coefficient) to measure the reliability and validity of smartphone use. Smartphone use was also compared with four other existing methods. This study demonstrated that the developed model achieved the best performance in terms of a correlation coefficient.

The obtained results show that, by using two Android smartphone devices with insole shoe sensors, a high level of agreement was obtained, allowing for a good range of acceptable alternatives to assess spatiotemporal parameters. Besides, our findings demonstrate that the smartphone can be used as a reliable and valid tool in spatiotemporal gait analysis of healthy adults. This method can help clinicians to work more efficiently, and to objectively evaluate gait with easy to use and interesting work as well as reduce cost. A future work is needed to investigate the ability of smartphones to detect the differences between adults and older people in their way of walking and to ascertain whether it is sensitive enough to detect differences in gait patterns. Furthermore, we can apply big data and different devices to study the spatiotemporal parameters of the insole sensors and smartphones for healthy and non-healthy people.

We compared the developed method with some existing methods based on validation studies and other well-known methods. The following studies presents the comparison of performances among the developed methods and the other four reported methods (Furrer et al 2015; Park and Kim 2018; Hollman et al. 2016; Clark et al, 2016).

Regarding the validation study, Furrer et al. (2015) proposed the same method of validation as our study; a smartphone device used to compare the motion capture systems. In their study, 22 healthy young adults were assessed with a smartphone application and a motion capture system. The reliability of their proposed method was evaluated using the correlation coefficient and standard error. The validity of the smartphone application and motion capture-derived values were compared with the Pearson correlation coefficient and Bland-Altman limits of agreement. They demonstrated that there was agreement in the obtained results of the systems.

Another study was presented by Park and Kim (2018) in which the reliability and validity of a smartphone-based accelerometer in quantifying spatiotemporal gait parameters of stroke patients when attached to the body were confirmed. In their study, the gait parameters were measured and evaluated using a smartphone accelerometer and GAITRite analysis. Thirty participants were asked to walk 10 meters. Then three parameters: gait velocity, cadence and step length were computed using smartphone-based accelerometers. The results were validated with a GAITRite analysis system. Average excellent reliability (ICC2 $\geq$.98) of correlation coefficient was reported. They observed that a high correlation between the smartphone-based gait parameters and the GAITRite analysis system-based gait parameters was achieved.

To provide a more thorough evaluation of the developed method, it was also compared with existing studies in the literature most of the studies utilizing a smartphone device to study the gait parameters applied one or two measurements to evaluate the obtained data. It was also found that many studies were conducted with a limited number of subjects using limited trials to compute gait parameters. Furthermore, these studies used only one or two measures to evaluate performance results. One of the studies was presented by Hollman et al. (2016). They developed a method for comparison of variability in spatiotemporal gait parameters between treadmill and overground walking conditions. In their study, 20 healthy participants aged between 22 and 27 years walked for 6 minutes on a treadmill and overground. A different set of parameters was used and measured in that study. They focused on the importance of the consideration of gait variability when using treadmills for research or clinical purposes because of its potential to lead to invariant gait patterns.

In 2013, Clark et al. provided a method to assess the validity of overground walking, recording the spatiotemporal data using a criterion reference-based three-dimensional motion analysis system. In their study, a different set of parameters (gait speed, step length and time, stride length, and time) were measured.
According to Clark et al. (2013), we used step time, stride time, cadence and walking speed for a comparison of spatiotemporal gait parameters between smartphone and insole sensors. Furthermore, the Bland-Altman 95% bias and limits of agreement, linear regression and statistical analysis using mean and SD were also employed to

evaluate the obtained measures and to assess the agreement between the two systems. The comparison between the devices showed excellent agreement.

In summary, from all the obtained results above, we can see that specific opportunities exist for smartphone-based gait assessment as an alternative to conventional gait assessment. Furthermore, a smartphone-based gait assessment could provide reliable information about changes in spatiotemporal gait parameters.

CHAPTER 6 CONCLUSION

This chapter introduces the overall findings of this research. In addition, it suggests some areas for future possible research.

6.1 Conclusion

As gait research using smartphone sensors continues to expand, new strategies and different ideas are offered in this research. This thesis shows that an accelerometer sensor in a smartphone can provide significant results in terms of accuracy in comparison to that of the photogrammetry technique and insole sensors. This new approach can be used widely in research and clinical environments to obtain accurate data for kinematics and kinetics. Our hypothesis assumed that smartphone devices could provide close readings and gait measurements comparable to the camera by taking the accelerometer reading as a parameter to compare the location of the limb during the stance phase of the gait. This part of the thesis is achieved the first objective of this research.

The current work concludes that accelerometer sensors embedded in the smartphone can be used as a significant and easy method to obtain gait characteristics. Moreover, the proposed application running on Android could be useful as a diagnostic aid tool for analysing human movement.

Even though the proposed method has some limitations, it can be considered a new, cheap and effective method; saving time, money and physical space compared to the photogrammetry technique.

The research also aimed to evaluate the smartphone technique design and implementation for measuring and studying participants' spatiotemporal gait parameters. To achieve second objective, a new methodology has been developed to study the spatiotemporal parameters of healthy people: step time, stride time, cadence and walking speed, using both insole sensors and smartphones.

In this research, an innovative method to analysis spatiotemporal gait parameters was used to extract the most important features from 30 subjects. One of the most important findings was that the outcomes of the accelerometer sensor embedded in smartphone device was convergent to the insole shoe sensor's data when measuring spatiotemporal parameters. The effectiveness of the developed model was validated with two Android smartphones. Determine the suitability of new gait parameters characteristics to identify and relationship between Smartphone and Insole sensors achieved objective three.

Objective four has been achieved by evaluate and validate the performance quality of the proposed methods, this study used different statistical methods (ANOVA, Bland-Altman, linear regression, and Pearson correlation coefficient) to measure the reliability and validity of smartphone use. Smartphone use was also compared with four other existing methods. It was demonstrated that the developed model had better readings in terms of a correlation coefficient.

The obtained results showed that, by using two Android smartphone devices with insole shoe sensors, a high level of agreement was obtained, allowing for a good range of acceptable alternatives to assess spatiotemporal parameters. Our findings demonstrate that the smartphone can be used as a reliable and valid tool in the spatiotemporal gait analysis of healthy adults. This method can help clinicians evaluate gait more efficiently, objectively and with greater ease; provide interesting work as well as reducing cost.

6.2 Future work

We believe that this research can be developed further to play a role in changing the way gait assessment is conducted in the fields of sport, rehabilitation, etc. There are possibilities of future research related to the concept explored in this thesis. First, developing new algorithm to interpret the accelerometer in terms of position and acceleration.

Second, additional studies will be needed to investigate the ability of smartphones to detect the differences between adults and older people in their way of walking and to ascertain whether it is sensitive enough to detect differences in gait patterns.

Third, future research can focus on using new smartphones applications with different sensors. The findings could also be used to develop new techniques for sport and exercise purposes.

Fourth, big data may also be applied to different devices to study the spatiotemporal parameters of insole sensors and smartphones for healthy versus non-healthy people and women versus men.

Fifth, many other human gait characteristics can be examined using this new approach. For instance, cadence, stride length, step length, stance time and EMG.

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APPENDIX A

Ethics Clearance Forms

A.1 Participant Information Sheet

To: Participants

Full Project Title: Biomechanical measures from using smart body-wear sensors for gait analysis

Principal Supervisor: Dr. Albert Chong

Principal Researcher: Mustafa Al-lami

I am a PhD student at the University of Southern Queensland and my research is related to the area of analyse human gait by using smartphone and floor and insole shoes sensors. Through my PhD, I aim to introduce an alternative methodology to conduct human gait studies. I identified a gap in the research in this area and I believe that through my research I will be able to provide an alternative, cheap and easy to use method for gait movement study by using Smartphone. It will help the resrachees and the normal people to study and know the gait characteristic. I would therefore like to invite you to take part in this research project.

You are invited to participate in this research project because I believe that this research will be beneficial for the health assessment and sport and most of researches that are related with study human movement.

Please read the following statements carefully. They have been written to explain all the procedures involved so you can make a fully informed decision to participate or not. Feel free to ask questions about any information in the document. You may also wish to discuss the project with a relative, friend or doctor.

Once you understand what the project is about and agree to take part in it, please sign the Consent Form. By signing the Consent Form, you indicate that you have understood the information and that you give your consent to participate in the research project.

1. Purpose of Research

The propose of this research is to develop a set of body wear-based biomechanical measures for gait characteristic study. The suggested method will help experts to reduce time, effort and money. This research is a part of a PhD degree.

2. Procedure

Participation in this project will involve:

- **Visiting the venue**

Participants need to come to the Photogrammetry lab which is located on the ground floor in S block at USQ/Toowoomba.

- P**reparation for pressure capturing**

Participants walk with smartphone attached on his/her leg. Also will be given appropriate sized shoes with insole sensors inside them, and then be connected to a computer.

- **Smartphone and Pressure recording**

Participants will be asked to walk along the lab (about 10 metres) to record the Smartphone data and pressure beneath the feet.

- **After recording**

One of the investigators will remove the smartphone and the shoes with the sensors. The whole experiment will take approximately 20-30 minutes. Some basic characteristics will be recorded about each participant, namely: age, gender, height and weight. All the researchers involved in this study will be available during the study to provide assistance and answer any participant questions. The participants will be a part of a novel study and if they wish to have any follows ups on the final results of the study, they can contact the researchers. There will be almost no any kind of risks during the trials as the participants will be walking at their normal speed and the researchers will make sure that the walkway is clear. In addition, this research does not involve any kind of health or foot assessment.

3. Confidentiality

The raw pressure and smartphone records for each participant will be immediately downloaded and then stored in a password protected research computer at USQ, which no one has access to other than the researchers involved in the study. The data will be stored until the PhD studies have been completed. Any information obtained in connection with this project that can identify participants will remain confidential. Personal information such as names or images that can lead to the identification of the participant will not be included at any stage of this study. Information regarding gender and weight of participants may be published but information regarding participant identity will be removed.

4. Voluntary Participation

Participation is entirely voluntary. If you do not wish to take part you are not obliged to. If you decide to take part and change your mind later, you are free to withdraw from the project at any stage. Any information already obtained from you will be destroyed. Before you make your decision, a member of the research team will be available to answer any questions you have about the research project. You can ask about any information you want. Sign the Consent Form only after you have had a chance to ask questions and have received satisfactory answers.

5. Queries or Concerns

Should you have any queries regarding the progress or conduct of this research, you can contact the principal researcher:

Dr. Albert Chong
Faculty of Engineering and Surveying
Room Z412
University of Southern Queensland
Tel (+61) 7 4631 2546 , Mobile: 0420534762

If you have any concerns or complaints about the ethical conduct of the project you may contact the University of Southern Queensland Manager of Research Integrity and Ethics on +61 7 4631 2214 or email researchintegrity@usq.edu.au.

A.2 Consent Form

To: Participants

Project Details

Full Project Title: Biomechanical measures from using smartphone sensors for gait analysis

Research Team Contact Details

Principal Investigator Details	**Supervisor Details**
Mustafa Al-lami Mobile: 0470019362 u1070577@umail.usq.edu.au	Dr. Albert Chong Mobile: 0420534762 Albertkon-fook.chong@usq.edu.au

- Have read and understood the information document regarding this project. ☐Yes / ☐No
- Have had any questions answered to your satisfaction. ☐Yes / ☐No
- Are over 18 years of age? ☐Yes / ☐No
- Understand that if you have any additional questions, you can conta research team. ☐Yes / ☐No
- I understand that while information gained during the study may be published, I will not be identified and my personal results will remain confidential. ☐Yes / ☐No
- Agree to participate in the project. ☐Yes / ☐No

By signing below, you are indicating that you:

Participant Name	
Participant Signature	
Date	

Please return this sheet to a Research Team member prior to undertaking the focus group.

- ✓ I have read the Participant Information Sheet and the nature and purpose of the research project has been explained to me. I understand and agree to take part.
- ✓ I understand the purpose of the research project and my involvement in it.
- ✓ I understand that I may withdraw from the research project at any stage and that this will not affect my status now or in the future.
- ✓ I confirm that I am over 18 years of age.
- ✓ I understand that while information gained during the study may be published, I will not be identified and my personal results will remain confidential.
- ✓ I understand that the scan recorded of my plantar surface during the research will be stored in a password protected computer at the University of Southern Queensland and access will only be granted to the researchers involved in the study.

Name of participant..

Signature..............................   Date.................

If you have any concerns or complaints about the ethical conduct of the project you may
contact the University of Southern Queensland Manager of Research Integrity and Ethics on
+61 7 4631 2214 or email researchintegrity@usq.edu.au.

Appendix B

Qualysis and photogrammetry results

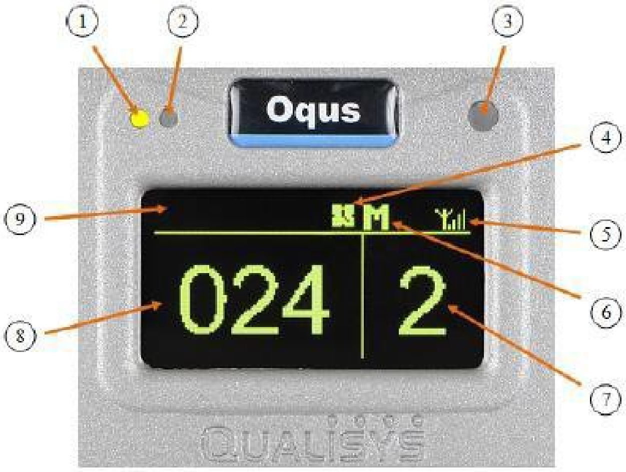
B.1 Qualysis track manager setting up process and specifications

1. **Left Data port, Right Data port** (light blue)
   Ethernet connector. 100BaseTX/802.3i, 100 Mbps, Fast Ethernet. The two ports are identical.
2. **Left Ethernet activity indicator, Right Ethernet activity indicator**
   Shows the status of the Ethernet connection. Fixed green light means that a carrier signal has been detected and that the connection is up. Flashing green light indicates that data is received and/or transmitted.
3. **Battery port** (white)
   Used to supply the camera with power from an Oqus compatible battery.
4. **Battery status indicator**
   Lit green when the camera is supplied though the **BATTERY** port.
   Lit red when a voltage outside the specified range (10-16V) is connected to the port.
5. **Power supply status**
   Lit green when the camera is powered through one of the **POWER** ports. A red light indicates internal power supply error.
6. **Left power supply port, Right power supply port** (black)
   Daisy-chain power port. Supplies the camera with 48VDC and can be daisy chained to supply cameras further down the chain with power. The ports are identical there is no specific in-port or out-port.
7. **Control port** (light grey)
   The control port is used to synchronize the camera with external sources, and contains pins for e.g. external trigger in, external sync in and external sync out. Splitter cables are needed to connect one or more BNC cables to this port.
8. **Camera identification**
   This label provides information on:
   - The serial number of the camera
   - The product number
   - The Ethernet Mac address
   - The WLAN Mac address

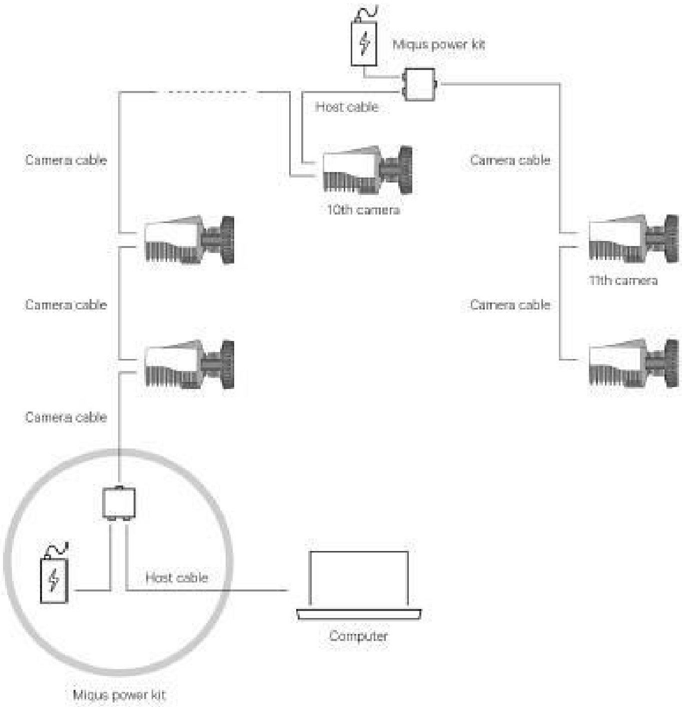
Oqus camera display

The Oqus camera has a large graphical OLED display and three LEDs on the front to inform the user of the current status of the camera. The display shows, among other things, the camera number and the number of markers currently seen by the camera.

Note: The display will be turned off when the camera enters stand-by mode, i.e. if the camera has not been in use for 2 hours. Start a preview in QTM to light up the display again.



1. **Measurement status indicator**
   Green light - The camera is ready to start a measurement
   Yellow light - The camera is measuring
   Flashing green light - Waiting for trigger to start measurement
   Flashing yellow light - Waiting for trigger to switch from pre-trigger to post-trigger measurement
2. **Error indicator**
   A red light indicates that an error has occurred. The LED is blinking when a software error occurs and is lit constantly if a hardware error occurs.
3. **IR receiver**
   The IR receiver is used for synchronization with certain active markers. It detects modulated light with a frequency of 33 kHz and is sensitive to light with wavelengths between 800 and 1100nm.
4. **Synchronization status**
   During the synchronization phase this symbol is flashing. When the camera is synchronized with the master camera in the system it becomes stable.
5. **WLAN indicator**
   This symbol is displayed when the WLAN of the camera is activated.
6. **Master/Slave indicator**
   An M indicates that the camera is master for the system and by that controls for example internal synchronization. An S indicates that the camera is a slave. The indicator can also be a rotating + sign, which means that the camera is looking for the Master camera.

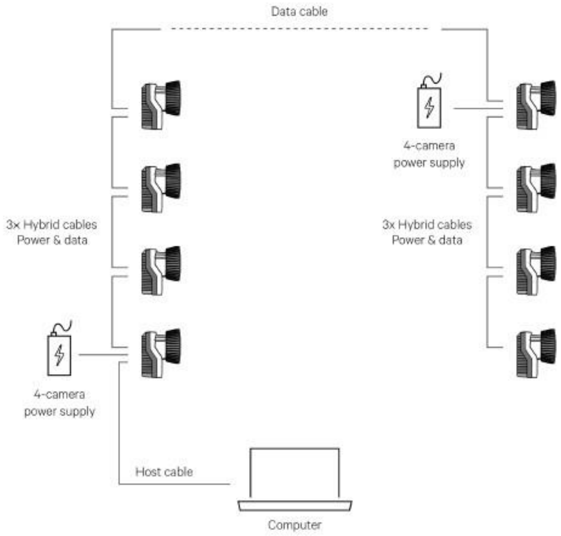


When the cables have been connected correctly, the indicator LEDs at the Miqus data/power ports will be lit as indicated in the illustration below. For more information about the connectors and the function of the indicators, see the Sections "Miqus camera: front side" on the facing page and "Miqus camera: back side" on page 12.

Note: For more detailed information about the Miqus system, please refer to the QTM manual or the Miqus setup guide.

Note: When the cables have been connected correctly the LEDs on the back of the Oqus will be lit. The **EXT** LED will be lit green and the **ACT** LEDs will be blinking.

However, the connection of the power adapters does require some attention. One power adapter can power up to 4 Oqus cameras. Therefore, the connection of a camera system comprising of more than four cameras must look something like the image below.



This means that you must use the following cables for an 8 camera system:

1 host cable between computer and camera.

6 bundled cables with power and data.

1 data cable connected between camera 4 and 5 in the setup, because one AC/DC adapter can only power 4 cameras.

2 AC/DC adapters, connected to for example camera 1 and 5.

Note: For more detailed information about the Oqus system, please refer to the QTM manual or the Oqus setup guide.

Oqus connectors

The back of the camera holds six connectors for power, data and control connections. The view differs slightly depending on the type of camera. The image below shows the standard version of the camera. The water protected version uses different connectors and lacks the LEDs found on the standard version.

B.2 Result of camera parameter after run the bundle in the Australis program

Australis Bundle Adjustment Results File: Bundle.txt

28 February, 2018 01:12:49

Quick Summary
Project: D:\PhD\18-1-2018 test\HSHSHSHSHSHSHSHS\C1\New folder\system calibration after run bundle.aus
Adjustment: Preferred control points specified
Simulated Network: No
Folding Method: Standard
Scaling: N/A
Units: mm
Number of Points: 49
Number of Images: 4
Number of Scale Bars: 0
Number of Iterations: 6
Elapsed CPU Time: 0.069 seconds

Adjusted Exterior Orientation Parameters (angles are decimal degrees, XYZ are mm)

Results for Station Image001 FileName 10.tif Camera camera 1 Lens

Station Variable	Initial Value	Total Adjustment	Final Value	Initial Standard Error	Final Standard Error
X	494.0622	31.6230	525.6853	1.0000E+003	1.6972E+001
Y	2051.8775	-11.2287	2040.6488	1.0000E+003	1.8076E+001
Z	1904.4410	-77.8125	1826.6285	1.0000E+003	4.4889E+001
AZ	-178.6760	2.2615	-176.4145	1.0000E+003	9.7939E-001
EL	-64.9149	0.0753	-64.8396	1.0000E+003	4.5755E-001
ROLL	180.4669	-2.0742	178.3927	1.0000E+003	9.1646E-001

Results for Station Image002 FileName 10.tif Camera camera 2 Lens

Station Variable	Initial Value	Total Adjustment	Final Value	Initial Standard Error	Final Standard Error
X	1105.9302	2.9359	1108.8661	1.0000E+003	5.1826E+000

Y	1613.4308	-29.9528	1583.4780	1.0000E+003	6.7286E+000
Z	1598.8974	-186.7591	1412.1383	1.0000E+003	1.8386E+001
AZ	131.2186	-3.8940	127.3246	1.0000E+003	5.6107E-001
EL	-68.4245	2.9299	-65.4946	1.0000E+003	2.4996E-001
ROLL	-133.4908	3.4881	-130.0027	1.0000E+003	5.9794E-001

Results for Station Image003 FileName 10.tif Camera camera 3 Lens

Station Variable	Initial Value	Total Adjustment	Final Value	Initial Standard Error	Final Standard Error
X	1110.5142	13.6875	1124.2018	1.0000E+003	9.7756E+000
Y	2050.0382	-49.0996	2000.9386	1.0000E+003	1.6225E+001
Z	2103.0787	-136.5942	1966.4845	1.0000E+003	4.5359E+001
AZ	134.9721	-0.6003	134.3718	1.0000E+003	1.0587E+000
EL	-65.6355	-0.6527	-66.2882	1.0000E+003	4.6096E-001
ROLL	-134.3709	0.7794	-133.5915	1.0000E+003	1.0528E+000

Results for Station Image004 FileName 10.tif Camera Camera 4 Lens

Station Variable	Initial Value	Total Adjustment	Final Value	Initial Standard Error	Final Standard Error
X	531.6483	35.3051	566.9534	1.0000E+003	1.5578E+001
Y	1683.4639	0.9659	1684.4297	1.0000E+003	9.8792E+000
Z	1669.5326	-68.8904	1600.6422	1.0000E+003	3.5557E+001
AZ	-168.1994	2.6009	-165.5985	1.0000E+003	1.2180E+000
EL	-76.2523	0.0036	-76.2487	1.0000E+003	2.9025E-001
ROLL	174.8448	-2.4672	172.3776	1.0000E+003	1.1862E+000

Summary of Image Coordinate Residuals (units are micrometres)

Sta #	RMS of Image Residuals x	y	xy	Number of non-rejected points
Image001	2.52	2.61	2.57	49
Image002	8.06	5.09	6.74	47
Image003	3.25	3.44	3.35	49
Image004	3.03	3.30	3.17	49

Total Residuals (RMS) x	y	xy	Sigma0	Degrees of Freedom	Observations	Parameters	Constraints
4.73	3.71	4.25	10.533	286	388	211	109

Standard Errors From Limiting Error and Total Error Propogation (XYZ are in mm)

11111111112222222223

123456789012345678901234567890

	Limiting Sigma Estimates			Total Sigma Estimates				Sightings	
Label	sX	sY	sZ	sX	sY	sZ	RMS	Rays #	List
A1	0.4336	0.4177	0.8435	0.4448	0.4313	0.8483	3.2	4	YYYY
A2	0.3166	0.3866	0.8810	0.3189	0.3925	0.8841	3.1	4	YYYY
A3	0.2743	0.3858	0.9659	0.2755	0.3905	0.9695	3.7	4	YYYY
A4	0.3033	0.4113	1.0729	0.3055	0.4192	1.0814	4.4	4	YYYY
A5	0.3838	0.4033	0.8839	0.3867	0.4074	0.8908	3.9	3	YNYY
A6	0.5298	0.4370	0.8583	0.5486	0.4483	0.8751	3.3	3	YNYY
B1	0.4293	0.3246	0.8407	0.4373	0.3285	0.8442	3.7	4	YYYY
B2	0.3153	0.3174	0.9055	0.3169	0.3191	0.9078	5.4	4	YYYY
B3	0.2746	0.3329	1.0071	0.2753	0.3344	1.0095	4.4	4	YYYY
B4	0.2938	0.3330	0.9994	0.2949	0.3344	1.0030	4.0	4	YYYY
B5	1.8086	1.0283	5.0453	1.9145	1.0902	5.3141	1.2	4	YYYY
B6	0.4412	0.3203	0.9037	0.4548	0.3248	0.9175	11.3	4	YYYY
C1	0.3587	0.2952	1.0112	0.3605	0.2965	1.0138	5.0	4	YYYY
C2	0.3195	0.3229	1.1595	0.3206	0.3246	1.1634	4.0	4	YYYY
C3	0.2804	0.2946	0.9418	0.2812	0.2954	0.9441	3.0	4	YYYY
C4	0.3253	0.3449	1.2058	0.3267	0.3467	1.2125	3.9	4	YYYY
C5	0.3856	0.2914	0.8398	0.3918	0.2938	0.8473	6.7	4	YYYY
C6	0.4269	0.2953	0.9899	0.4337	0.2968	1.0009	4.0	4	YYYY
D1	0.3712	0.3045	1.1604	0.3738	0.3059	1.1662	3.0	4	YYYY
D2	0.3261	0.3013	0.9537	0.3271	0.3023	0.9563	3.3	4	YYYY
D3	0.2922	0.3000	1.0641	0.2927	0.3006	1.0665	4.3	4	YYYY
D4	0.3128	0.3074	1.0725	0.3134	0.3079	1.0753	4.5	4	YYYY
D5	0.3664	0.3024	0.9430	0.3680	0.3033	0.9471	6.9	4	YYYY
D6	0.4754	0.3157	1.1350	0.4853	0.3173	1.1530	1.8	4	YYYY
E1	0.3528	0.3326	1.0463	0.3545	0.3340	1.0513	5.2	4	YYYY
E2	0.3318	0.3927	0.8983	0.3336	0.3964	0.9036	3.8	4	YYYY
E3	0.3102	0.3437	1.2058	0.3111	0.3448	1.2125	3.2	4	YYYY
E4	0.3075	0.3867	0.8985	0.3091	0.3895	0.9049	5.5	4	YYYY
E5	0.4151	0.3623	1.1979	0.4188	0.3638	1.2105	4.6	4	YYYY
E6	0.4439	0.3396	1.0282	0.4493	0.3409	1.0399	1.3	4	YYYY
F1	0.3412	0.4125	0.9730	0.3427	0.4158	0.9796	2.2	4	YYYY
F2	0.3080	0.3950	1.0746	0.3089	0.3966	1.0802	1.3	4	YYYY
F3	0.3098	0.4241	1.2150	0.3108	0.4263	1.2244	1.3	4	YYYY
F4	0.3420	0.4334	1.2096	0.3435	0.4357	1.2207	2.3	4	YYYY
F5	0.3810	0.4088	1.0630	0.3829	0.4103	1.0709	4.5	4	YYYY
F6	0.4290	0.4365	0.8748	0.4377	0.4418	0.8915	2.1	4	YYYY
G1	0.3380	0.5175	0.9510	0.3402	0.5275	0.9631	3.6	4	YYYY
G2	1.3790	2.5877	6.0697	1.4576	2.7346	6.3985	1.7	4	YYYY
G3	0.2789	0.4750	0.9907	0.2796	0.4776	0.9973	1.5	4	YYYY
G4	0.3197	0.4917	1.0818	0.3207	0.4946	1.0904	1.6	4	YYYY
G5	0.3628	0.4763	0.9705	0.3649	0.4792	0.9803	5.1	4	YYYY
G6	0.4195	0.4865	0.8887	0.4281	0.4933	0.9112	4.9	4	YYYY

H1	0.4698	0.6874	1.2485	0.4796	0.7092	1.2720	3.5	4	YYYY
H2	0.2949	0.5560	0.9571	0.2964	0.5651	0.9719	4.5	4	YYYY
H3	0.3155	0.6907	1.2272	0.3171	0.7090	1.2474	2.1	4	YYYY
H4	0.3109	0.5525	0.9299	0.3129	0.5586	0.9448	5.1	4	YYYY
H5	0.4541	0.7208	1.2117	0.4604	0.7413	1.2457	2.8	4	YYYY
H6	0.4287	0.5560	0.9074	0.4388	0.5660	0.9397	6.1	4	YYYY
X1	1.4970	1.4692	5.0936	2.1216	2.0211	7.6230	6.2	4	YYYY

	Summary of Limiting STD Error Estimates			Summary of Total STD Error Estimates		
	X	Y	Z	X	Y	Z
RMS is	0.5252	0.6059	1.6679	0.5810	0.6554	1.8968
Minimum is	0.2743	0.2914	0.8398	0.2753	0.2938	0.8442
at point	A3	C5	C5	B3	C5	B1
Maximum is	1.8086	2.5877	6.0697	2.1216	2.7346	7.6230
at point	B5	G2	G2	X1	G2	X1

Triangulated Object Space Coordinates (XYZ are in mm)

Label	X	Y	Z	RMS	# Rays	Sightings List 1111111111222222222223 123456789012345678901234567890
A1	1011.3783	1712.2738	150.8390	3.2	4	YYYY
A2	1112.0439	1711.7774	100.4227	3.1	4	YYYY
A3	1210.0959	1714.0532	50.8644	3.7	4	YYYY
A4	1309.9482	1712.2392	0.8039	4.4	4	YYYY
A5	1411.3322	1712.1270	99.8485	3.9	3	YNYY
A6	1510.5519	1711.4339	145.8114	3.3	3	YNYY
B1	1011.2194	1611.9687	150.8164	3.7	4	YYYY
B2	1110.7951	1613.1419	101.2311	5.4	4	YYYY
B3	1211.6672	1610.6812	50.7142	4.4	4	YYYY
B4	1311.4210	1611.7632	50.3983	4.0	4	YYYY
B5	1411.4801	1609.7261	-1.6264	1.2	4	YYYY
B6	1512.9587	1612.3734	99.9889	11.3	4	YYYY
C1	1010.2112	1511.7327	51.2587	5.0	4	YYYY
C2	1112.2263	1512.7401	0.8679	4.0	4	YYYY
C3	1210.7515	1510.8403	101.2299	3.0	4	YYYY
C4	1312.0139	1512.0872	0.2857	3.9	4	YYYY
C5	1410.2528	1510.6560	150.5421	6.7	4	YYYY
C6	1513.4752	1512.6529	50.4742	4.0	4	YYYY
D1	1011.1791	1414.9972	1.1706	3.0	4	YYYY
D2	1110.9097	1413.3874	101.7315	3.3	4	YYYY
D3	1211.4202	1410.9622	51.7052	4.3	4	YYYY
D4	1311.3023	1413.0895	50.4558	4.5	4	YYYY
D5	1409.9508	1410.2243	99.5671	6.9	4	YYYY

D6	1511.1047	1411.8392	-0.2930	1.8	4	YYYY
E1	1011.1869	1314.0159	51.7520	5.2	4	YYYY
E2	1111.8407	1312.3194	150.6501	3.8	4	YYYY
E3	1209.9275	1313.4849	1.4785	3.2	4	YYYY
E4	1310.3674	1311.5187	150.1894	5.5	4	YYYY
E5	1410.2494	1312.5926	-1.1484	4.6	4	YYYY
E6	1511.6614	1313.1157	50.2526	1.3	4	YYYY
F1	1011.0644	1215.2142	101.3107	2.2	4	YYYY
F2	1111.9130	1212.9185	50.9926	1.3	4	YYYY
F3	1209.5947	1212.2189	0.2239	1.3	4	YYYY
F4	1310.4292	1213.3041	-0.1950	2.3	4	YYYY
F5	1410.7916	1213.6279	49.9369	4.5	4	YYYY
F6	1512.1375	1211.6500	149.7517	2.1	4	YYYY
G1	1010.7045	1114.6164	151.7798	3.6	4	YYYY
G2	1112.0814	1112.5242	-2.0833	1.7	4	YYYY
G3	1210.6858	1113.4515	100.8072	1.5	4	YYYY
G4	1309.6892	1113.9872	50.0884	1.6	4	YYYY
G5	1411.5941	1112.0403	98.9060	5.1	4	YYYY
G6	1510.2582	1112.6847	151.0154	4.9	4	YYYY
H1	1011.0155	1013.8087	1.1017	3.5	4	YYYY
H2	1109.8906	1012.2663	149.3401	4.5	4	YYYY
H3	1210.4006	1011.4572	0.1729	2.1	4	YYYY
H4	1311.8976	1011.6697	148.6562	5.1	4	YYYY
H5	1410.0879	1012.6985	0.2239	2.8	4	YYYY
H6	1509.6270	1012.1278	150.5631	6.1	4	YYYY
X1	467.8873	1439.4265	59.6043	6.2	4	YYYY

Image Coordinate Rejections

Image Number Image001

Image Number Image002

Image Number Image003

Image Number Image004

Total Rejections 0

Australis Bundle Adjustment Results: Camera Parameters

29 February, 2018 22:59:47

Project: D:\PhD\18-1-2018 test\HSHSHSHSHSHSHSHS\C1\New folder (25)\after run bundle 25.aus

Adjustment: Explicit Object Point Control
Number of Points: 49
Number of Images: 4
RMS of Image coords: 69.83 (um)

Results for Camera 1 camera 1 Lens

Sensor Size		Pixel Size (mm)
H	1920	0.003
V	1080	0.003

Camera Variable	Initial Value	Total Adjustment	Final Value	Initial Std. Error	Final Std. Error
C	4.5858	0.00000	4.5858	1.0e+003	1.102e-001 (mm)
XP	-0.0569	0.00000	-0.0569	1.0e+003	4.980e-002 (mm)
YP	-0.0452	0.00000	-0.0452	1.0e+003	4.321e-002 (mm)
K1	1.50717e-026	0.000e+000	1.50717e-026	1.0e-016	1.061e-015
K2	5.87099e-026	0.000e+000	5.87099e-026	1.0e-016	1.061e-015
K3	2.03330e-025	0.000e+000	2.03330e-025	1.0e-016	1.061e-015
P1	.92816e-027	0.000e+000	4.92816e-027	1.0e-016	1.061e-015
P2	-1.90732e-026	0.000e+000	-1.90732e-026	1.0e-016	1.061e-015
B1	4.68734e-027	0.000e+000	4.68734e-027	1.0e-016	1.061e-015
B2	1.57275e-027	0.000e+000	-1.57275e-027	1.0e-016	1.061e-015

Results for Camera 2 camera 2 Lens

Sensor Size		Pixel Size (mm)
H	1920	0.003
V	1080	0.003

Camera Variable	Initial Value	Total Adjustment	Final Value	Initial Std. Error	Final Std. Error
C	4.3383	0.00000	4.3383	1.0e+003	5.445e-002 (mm)
XP	0.0702	0.00000	0.0702	1.0e+003	3.136e-002 (mm)
YP	0.0149	0.00000	0.0149	1.0e+003	1.698e-002 (mm)
K1	2.49651e-003	0.000e+000	2.49651e-003	1.0e-016	1.061e-015
K2	-3.60700e-004	0.000e+000	-3.60700e-004	1.0e-016	1.061e-015
K3	6.24184e-005	0.000e+000	6.24184e-005	1.0e-016	1.061e-015
P1	-6.97313e-027	0.000e+000	-6.97313e-027	1.0e-016	1.061e-015
P2	-3.14540e-026	0.000e+000	-3.14540e-026	1.0e-016	1.061e-015
B1	5.27556e-027	0.000e+000	5.27556e-027	1.0e-016	1.061e-015
B2	-2.40271e-027	0.000e+000	-2.40271e-027	1.0e-016	1.061e-015

Results for Camera 3 camera 3 Lens

Sensor Size		Pixel Size (mm)
H	1920	0.003
V	1080	0.003

Camera Variable	Initial Value	Total Adjustment	Final Value	Initial Std. Error	Final Std. Error
C	4.7348	0.00000	4.7348	1.0e+003	1.002e-001 (mm)
XP	0.0234	0.00000	0.0234	1.0e+003	5.605e-002 (mm)
YP	-0.0778	0.00000	-0.0778	1.0e+003	2.868e-002 (mm)
K1	1.12491e-026	0.000e+000	1.12491e-026	1.0e-016	1.061e-015
K2	6.03811e-026	0.000e+000	6.03811e-026	1.0e-016	1.061e-015
K3	2.98818e-025	0.000e+000	2.98818e-025	1.0e-016	1.061e-015
P1	-4.37766e-027	0.000e+000	-4.37766e-027	1.0e-016	1.061e-015
P2	-1.71553e-026	0.000e+000	-1.71553e-026	1.0e-016	1.061e-015
B1	4.06085e-027	0.000e+000	4.06085e-027	1.0e-016	1.061e-015
B2	3.06112e-028	0.000e+000	3.06112e-028	1.0e-016	1.061e-015

Results for Camera 4 Camera 4 Lens

Sensor Size		Pixel Size (mm)
H	1920	0.003
V	1080	0.003

Camera Variable	Initial Value	Total Adjustment	Final Value	Initial Std. Error	Final Std. Error
C	4.7245	0.00000	4.7245	1.0e+003	1.029e-001 (mm)
XP	0.2793	0.00000	0.2793	1.0e+003	4.461e-002 (mm)
YP	-0.0257	0.00000	-0.0257	1.0e+003	3.004e-002 (mm)
K1	8.71764e-027	0.000e+000	8.71764e-027	1.0e-016	1.061e-015
K2	2.70215e-026	0.000e+000	2.70215e-026	1.0e-016	1.061e-015
K3	7.45787e-026	0.000e+000	7.45787e-026	1.0e-016	1.061e-015
P1	-1.41018e-027	0.000e+000	-1.41018e-027	1.0e-016	1.061e-015
P2	-1.57898e-026	0.000e+000	-1.57898e-026	1.0e-016	1.061e-015
B1	3.92742e-027	0.000e+000	3.92742e-027	1.0e-016	1.061e-015
B2	-1.16692e-027	0.000e+000	-1.16692e-027	1.0e-016	1.061e-015

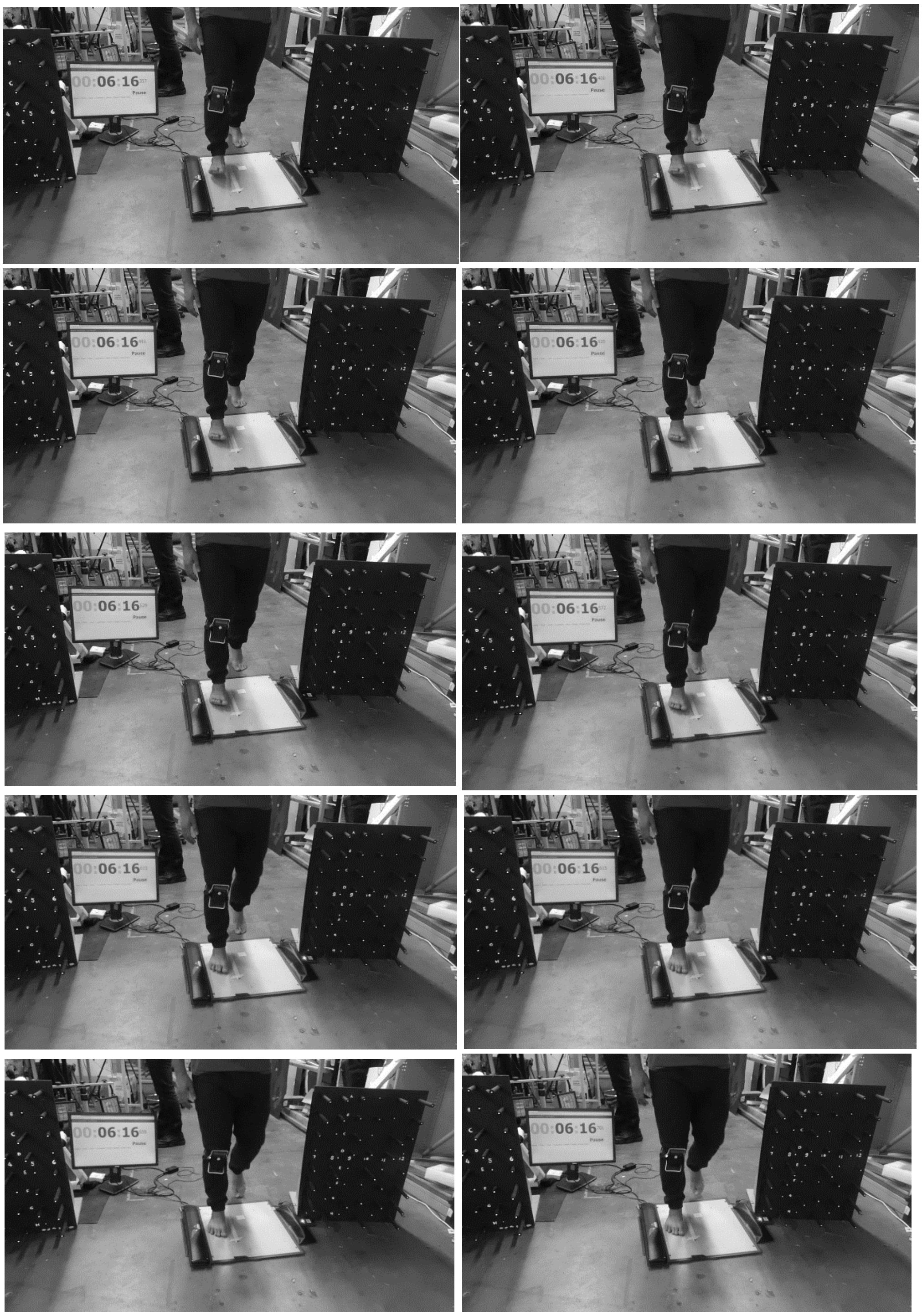
Maximum Observational Radial Distance Encountered: 3.0 mm

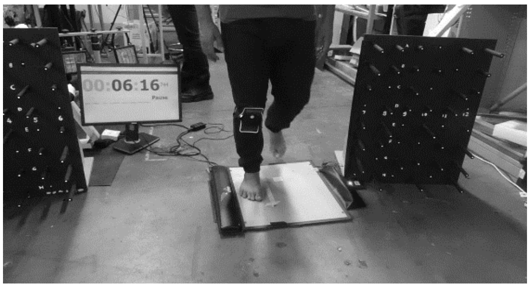
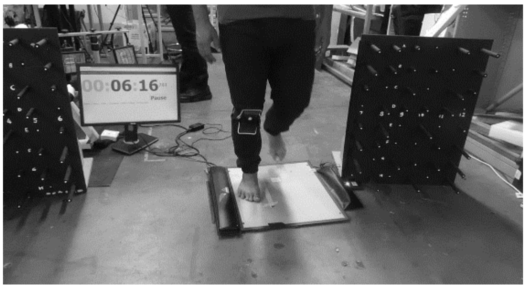
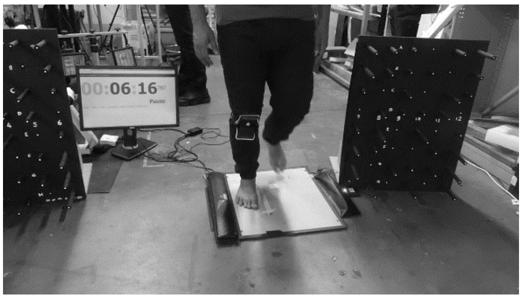
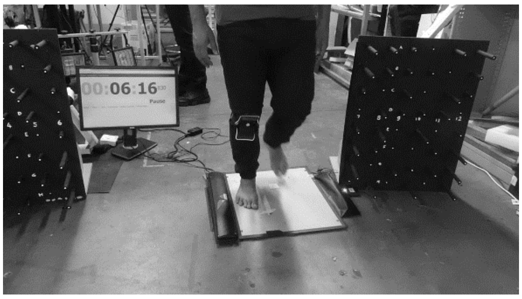
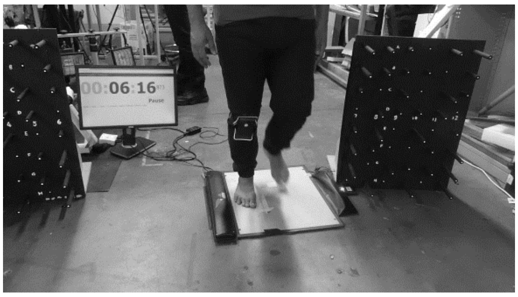
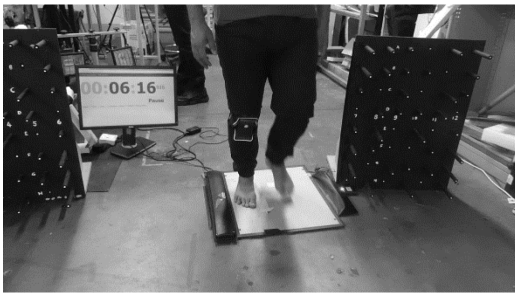
Exterior Orientation Summary (Xc, Yc, Zc are in project units, rotations are in decimal degrees)

Station	Image	Xc	Yc	Zc	Alpha	Elev.	Roll
1	Image001	493.73783	2051.69210	1904.78058	-178.660151	-64.922407	-179.553377
2	Image002	1106.02187	1613.51334	1598.82342	131.212108	-68.420315	-133.486112

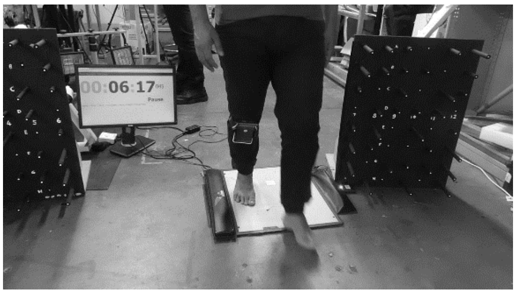
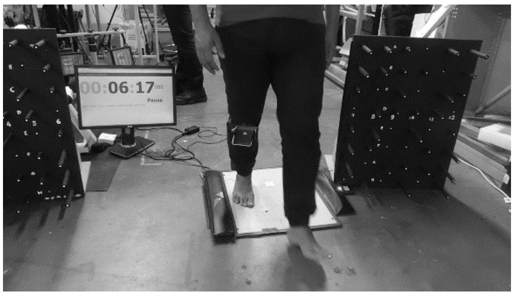
3 Image003 1109.97466 2050.74193 2102.71948 135.027579 -65.633688 -134.435997
4 Image004 532.35866 1682.25214 1669.27416 -168.223621 -76.285393 174.897834

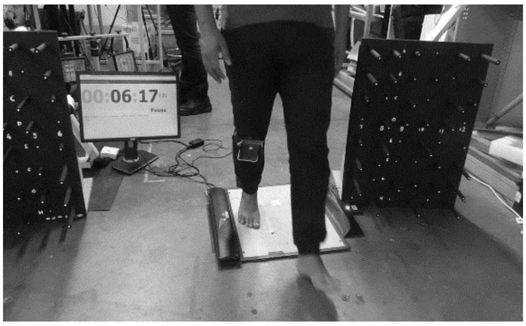
B.3 25 Photos of one step for one subject from one camera only.




00:06:16

00:06:16

00:06:16

00:06:16

00:06:16

00:06:16

00:06:16

00:06:17

00:06:17

00:06:17


00:06:17

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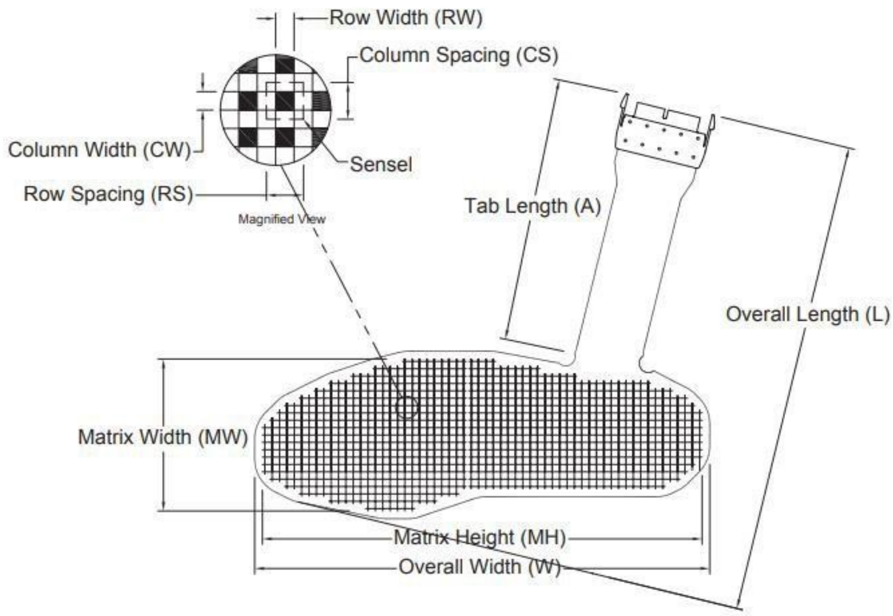
Appendix C

C.1 Insole sensors specification

Tekscan® Medical Sensor 3000E

PRESSURE MAPPING, FORCE MEASUREMENT, AND TACTILE SENSORS



General Dimensions			Sensing Region Dimensions								Summary	
Overall Length *L*	Overall Width *W*	Tab Length *A*	Matrix Width *MW*	Matrix Height *MH*	Columns			Rows			Total No. of Sensels	Sensel Spatial Resolution
					CW	Pitch *CS*	*Qty.*	*RW*	Pitch *RS*	*Qty.*		
(mm) 327.2	(mm) 313.7	(mm) 182.6	(mm) 106.7	(mm) 304.8	(mm) 2.5	(mm) 5.1	21	(mm) 2.5	(mm) 5.1	60	954	(sensel per sq-cm) 3.9
(in) 12.88	(in) 12.35	(in) 7.19	(in) 4.20	(in) 12.00	(in) 0.100	(in) 0.200	21	(in) 0.100	(in) 0.200	60	954	(sensel per sq-in) 25.0

Pressure Ranges

kPa	517	862
psi	75	125

C.2 results of 20 subjects left and right legs

Left						
		Insole		Smartphone		Insole VS Smartphone
Subjects	Variable	SD	Mean	SD	Mean	Preason R
1	Step time	0.02	0.73	0.02	0.74	0.69
	stride time	0.05	1.29	0.04	1.31	0.90
	Cadence	0.89	47.47	1.97	46.16	0.72
	Walking time	0.02	0.90	0.01	0.90	0.63
2	Step time	0.01	0.75	0.01	0.74	0.87
	stride time	0.02	1.31	0.02	1.30	0.65
	Cadence	0.59	47.10	0.75	45.37	0.66
	Walking time	0.01	0.90	0.02	0.89	0.93
3	Step time	0.11	0.71	0.08	0.69	0.96
	stride time	0.14	1.32	0.15	1.33	0.96
	Cadence	6.93	46.69	8.12	49.65	0.90
	Walking time	0.22	1.00	0.16	0.98	0.97
4	Step time	0.01	0.74	0.01	0.74	0.79
	stride time	0.03	1.26	0.05	1.27	0.87
	Cadence	1.18	47.56	1.92	47.19	0.85
	Walking time	0.01	0.90	0.03	0.90	0.70
5	Step time	0.02	0.70	0.04	0.68	0.91
	stride time	0.05	1.26	0.03	1.27	0.99
	Cadence	1.91	47.60	1.22	47.31	0.99
	Walking time	0.03	0.93	0.05	0.93	0.83
6	Step time	0.02	0.71	0.0	0.7	0.65
	stride time	0.01	1.30	0.0	1.3	0.79
	Cadence	2.83	50.07	2.5	47.8	0.68
	Walking time	0.01	0.92	0.01	0.9	0.79
7	Step time	0.01	0.71	0.02	0.78	0.76
	stride time	0.01	1.30	0.02	1.31	0.72
	Cadence	0.66	46.58	0.21	46.04	0.80
	Walking time	0.02	0.92	0.01	0.88	0.71
8	Step time	0.07	0.76	0.07	0.75	0.97
	stride time	0.19	1.31	0.22	1.25	0.95
	Cadence	6.16	47.38	6.56	50.77	0.87
	Walking time	0.05	0.88	0.06	0.90	0.83
9	Step time	0.01	0.75	0.01	0.75	0.87
	stride time	0.00	1.29	0.02	1.31	0.92
	Cadence	0.29	48.24	0.55	47.08	0.84
	Walking time	0.01	0.90	0.01	0.89	0.80
10	Step time	0.03	0.68	0.02	0.69	0.93
	stride time	0.02	1.26	0.03	1.27	0.92
	Cadence	1.57	48.10	1.22	47.31	0.97

	Walking time	0.02	0.95	0.01	0.95	0.96
11	Step time	0.03	0.66	0.04	0.63	0.96
	stride time	0.07	1.23	0.06	1.23	0.99
	Cadence	2.53	49.02	2.14	48.86	0.98
	Walking time	0.10	0.99	0.11	0.97	0.59
12	Step time	0.01	0.61	0.01	0.62	0.64
	stride time	0.02	1.18	0.01	1.18	0.87
	Cadence	0.41	50.94	0.54	50.70	0.90
	Walking time	0.03	1.10	0.03	1.09	0.71
13	Step time	0.03	0.60	0.04	0.61	0.69
	stride time	0.37	1.24	0.36	1.28	0.97
	Cadence	1.24	55.55	1.37	55.88	0.96
	Walking time	0.04	1.23	0.06	1.20	0.77
14	Step time	0.01	0.64	0.02	0.66	0.42
	stride time	0.04	1.17	0.03	1.18	0.72
	Cadence	1.75	50.84	0.97	50.30	0.72
	Walking time	0.05	0.97	0.08	0.97	0.73
15	Step time	0.03	0.64	0.03	0.61	0.87
	stride time	0.04	1.13	0.03	1.13	0.92
	Cadence	2.02	53.18	1.24	53.18	0.98
	Walking time	0.04	1.17	0.07	1.08	0.95
16	Step time	0.02	0.63	0.02	0.63	0.75
	stride time	0.03	1.11	0.02	1.11	0.96
	Cadence	1.56	54.06	1.20	53.96	0.96
	Walking time	0.04	1.22	0.08	1.22	0.68
17	Step time	0.02	0.64	0.04	0.58	0.96
	stride time	0.03	1.11	0.02	1.12	0.78
	Cadence	1.20	54.38	0.75	53.84	0.77
	Walking time	0.06	1.17	0.07	1.20	0.86
18	Step time	0.02	0.62	0.03	0.63	0.64
	stride time	0.03	1.11	0.02	1.11	0.79
	Cadence	1.45	54.40	1.32	54.64	0.98
	Walking time	0.09	1.15	0.10	1.12	0.76
19	Step time	0.02	0.61	0.05	0.56	0.07
	stride time	0.04	1.08	0.06	1.07	0.94
	Cadence	2.03	55.88	2.99	56.32	0.96
	Walking time	0.06	1.14	0.06	1.22	0.68
20	Step time	0.01	0.64	0.05	0.57	0.85
	stride time	0.01	1.10	0.03	1.13	0.95
	Cadence	1.17	54.58	1.06	53.96	0.66
	Walking time	0.06	1.34	0.029	1.330	0.91

Right						
		Insole		Smartphone		Insole Vs Smartphone
Subjects	Variable	SD	Mean	SD	Mean	Preason R
1	Step time	0.03	0.75	0.02	0.75	0.60
	stride time	0.05	1.30	0.07	1.33	0.90
	Cadence	1.58	46.50	2.08	45.53	0.85
	Walking time	0.02	0.91	0.02	0.91	0.69
2	Step time	0.01	0.76	0.01	0.75	0.87
	stride time	0.02	1.31	0.02	1.27	0.76
	Cadence	0.29	45.76	1.89	44.06	0.90
	Walking time	0.02	0.88	0.01	0.88	0.67
3	Step time	0.10	0.74	0.11	0.85	0.85
	stride time	0.19	1.31	0.19	1.30	0.98
	Cadence	6.99	46.43	6.88	46.84	0.99
	Walking time	0.12	0.93	0.10	0.87	0.74
4	Step time	0.02	0.72	0.01	0.74	0.65
	stride time	0.03	1.28	0.03	1.28	0.93
	Cadence	1.12	46.74	1.24	47.07	0.99
	Walking time	0.01	0.90	0.01	0.91	0.82
5	Step time	0.00	0.71	0.01	0.70	0.94
	stride time	0.04	1.25	0.04	1.23	0.95
	Cadence	1.63	48.16	1.36	48.64	0.93
	Walking time	0.03	0.90	0.01	0.93	0.85
6	Step time	0.01	0.72	0.05	0.75	0.74
	stride time	0.04	1.29	0.04	1.36	0.93
	Cadence	3.28	50.30	4.59	52.68	0.90
	Walking time	0.01	0.93	0.02	0.92	0.82
7	Step time	0.01	0.75	0.01	0.78	0.76
	stride time	0.00	1.30	0.02	1.30	0.87
	Cadence	0.12	46.30	0.45	45.75	0.83
	Walking time	0.02	0.88	0.01	0.89	0.74
8	Step time	0.06	0.77	0.09	0.81	0.91
	stride time	0.15	1.33	0.18	1.30	0.97
	Cadence	6.43	47.60	6.11	47.61	0.99
	Walking time	0.04	0.88	0.05	0.91	0.88
9	Step time	0.02	0.72	0.01	0.74	0.65
	stride time	0.02	1.29	0.03	1.28	0.89
	Cadence	0.35	47.37	0.91	47.01	0.76
	Walking time	0.01	0.92	0.01	0.90	0.88
10	Step time	0.01	0.70	0.01	0.70	0.65
	stride time	0.04	1.26	0.03	1.24	0.97
	Cadence	0.79	48.39	0.89	48.30	0.75
	Walking time	0.01	0.95	0.01	0.95	0.75
11	Step time	0.05	0.69	0.05	0.61	0.71
	stride time	0.07	1.22	0.02	1.19	0.74

	Cadence	2.54	49.25	0.98	50.70	0.72
	Walking time	0.04	1.00	0.06	0.99	0.98
12	Step time	0.01	0.62	0.02	0.62	0.65
	stride time	0.02	1.17	0.01	1.17	0.76
	Cadence	1.12	51.24	0.51	51.34	0.84
	Walking time	0.05	1.09	0.03	1.10	0.88
13	Step time	0.02	0.59	0.03	0.56	0.81
	stride time	0.15	1.14	0.06	1.10	0.94
	Cadence	1.55	56.29	1.97	56.22	0.97
	Walking time	0.08	1.22	0.05	1.21	0.74
14	Step time	0.02	0.65	0.01	0.66	0.82
	stride time	0.05	1.18	0.03	1.18	0.97
	Cadence	1.98	50.74	1.62	50.80	0.98
	Walking time	0.05	0.99	0.04	0.96	0.79
15	Step time	0.03	0.62	0.03	0.62	0.81
	stride time	0.04	1.15	0.03	1.14	0.67
	Cadence	1.90	52.76	1.46	52.90	0.68
	Walking time	0.04	1.16	0.08	1.08	0.94
16	Step time	0.01	0.64	0.02	0.63	0.90
	stride time	0.04	1.11	0.02	1.10	0.98
	Cadence	1.73	54.28	1.00	54.86	0.92
	Walking time	0.07	1.23	0.08	1.22	0.92
17	Step time	0.02	0.64	0.03	0.63	0.72
	stride time	0.02	1.12	0.01	1.13	0.86
	Cadence	0.95	53.80	0.50	53.18	0.87
	Walking time	0.04	1.15	0.05	1.16	0.67
18	Step time	0.01	0.62	0.02	0.62	0.73
	stride time	0.02	1.09	0.02	1.12	0.84
	Cadence	0.95	54.92	0.66	54.18	0.78
	Walking time	0.16	1.16	0.16	1.19	0.79
19	Step time	0.03	0.62	0.03	0.60	0.79
	stride time	0.04	1.07	0.04	1.07	0.99
	Cadence	2.23	56.32	2.40	55.98	0.98
	Walking time	0.12	1.18	0.08	1.22	0.88
20	Step time	0.01	0.63	0.03	0.62	0.79
	stride time	0.01	1.09	0.03	1.10	0.95
	Cadence	0.51	55.44	1.18	54.54	0.82
	Walking time	0.12	1.32	0.03	1.35	0.88