LOWER BODY GAIT ANALYSIS THROUGH REAL TIME GAIT PARAMETER MEASUREMENTS USING KINECT

By

BASHAR ABDULAZIZ MAHMOOD

A thesis submitted to the

Graduate School-New Brunswick

Rutgers, The State University of New Jersey

In partial fulfillment of the requirements

For the degree of

Master of Science

Graduate Program in Electrical and Computer Engineering

Written under the direction of

Yanyong Zhang

And approved by

____

____

____

New Brunswick, New Jersey

January 2015

ABSTRACT OF THE THESIS

Lower Body Gait Analysis Through Real Time Gait Parameter Measurements Using KINECT

By BASHAR ABDULAZIZ MAHMOOD

Thesis Director:

Prof. Yanyong Zhang

Gait analysis is one of the important areas of research, with applications including diagnosis, monitoring, and rehabilitation. Current gait analysis systems, such as those used in a laboratory or a clinic, are intrusive, expensive or require carefully tuned settings. This thesis presents an accurate low body gait analysis method that is low-cost, non-intrusive, and requiring no battery-powered sensors or markers. Instead, it conducts gait analysis using a Kinect sensor, which has been used in various research areas for its capabilities of obtaining full body gait information.

Our study uses the change in joint positions provided by the Kinect's virtual skeleton frames to extract lower body gait parameters. We propose a simple but efficient technique to measure stride and its two component intervals: stance and swing, using only the ankle joint of each leg. To measure the ground truth, we also build a wearable sensor that can obtain accurate stride information.

We evaluate our system using two subjects and report their stride duration, stance and swing intervals. Our results show that our system has a mean difference less than 10ms from the ground truth, with an error of less than 1%. Our results show that looking at the ankle joint alone is sufficient to calculate lower-body gait parameters.

Acknowledgement

I would express my deepest gratitude to my advisor, Prof. Yanyong Zhang, for her outstanding guidance, suggestions, and caring.

I would like to thank my sponsor, the Higher Committee for Education Development in Iraq (HCED), for their Financial and Academic supports, Advices, and all other facilities they offered to let me get the degree. Also, I would like to acknowledge, with much appreciation, the crucial role of my friends and my brother (Ayad) for their support during my scholarship duration.

Last, but not least, many thanks to my family and relatives for their great supports, prayers, and best wishes to me.

Table of contents

List of Tables

List of Illustrations

Chapter 1
Introduction

Human gait has been shown to be an important indication of health condition. Gait analysis is thus able to give reliable information on the development of various diseases: neurological diseases such as Parkinson's [1] or sclerosis [2], diabetes [3], and diseases caused by ageing such as fall risk [4], which have an effect on a large number of people. By monitoring and evaluating accurate, reliable gait data over time, an early diagnosis of diseases can be developed which will help patients to find the best solution.

A number of methods have been discussed for gait analysis. For example, marker-based systems usually use Infrared cameras to capture markers placed on the body. These systems are only appropriate for laboratory settings because markers, passive or active, must be fixed correctly on the body before each capture session. These systems are precise, but their cost is very high, and they are hard to move. There are other systems that are only found in laboratory settings. These use force plates and are usually expensive, and only measures gait parameters of the lower limbs.

Recently, several studies proposed systems that used wearable sensors [5], [6]. Such systems are less expensive, light-weighted, small-size, and mobile. These features make them more suitable in home ambulatory measurements. Despite these advantages, wearable sensors still have the disadvantage that sensors must be secured and correctly placed on the body [7]. In addition, gravity noise and signal drift must be considered [8]. Additionally, because of the very little gait information obtainable from a sensor, an array of sensors is used to get comprehensive measurements. In addition, wearable sensor systems are intrusive because they need changing due to the various types of subject's routines. Moreover, they need continuous maintenance, such as charging batteries, and transferring data.

Markerless visual gait analysis systems have been discussed by several studies. Recognizing individuals through their gaits using one or more RGB cameras has been studied by Goffredo and Bouchrika [9]. Leu et. al., worked on extracting the knee-joint angles, but stride parameters weren't obtained; their system requires complex setup and calibration of two cameras to produce a 3D image [28]. Both proposed systems are used to get lower body gait parameters only.

In this thesis, a low-cost, non-intrusive system has been suggested to accurately calculate some lower gait parameters using Kinect sensors and Software Development Kit (SDK). Kinect is a device produced by Microsoft Corporation. It consists of an array of sensors including: depth, RGB, IR camera sensors, and an array of speakers all packed at an affordable and compact device. Using depth camera, a 3D virtual skeleton of the body can be extracted [54]. Virtual Skeleton has 26 joints, each joint has its 3D coordinates that can be easily accessed by software. For these capabilities, several researchers have proposed to use it for home monitoring and gait analysis.

The first study that suggested to use Kinect for clinical gait analysis was presented by Stone and Skubic [55], [56] where objects at a height equal 50cm or less were located using the depth image. They concluded whether the left or the right foot was touching the ground using the volume of the objects. Gabel, et al. presented a full body gait analysis system by using information from the whole body to increase accuracy, and demonstrated how a rich set of parameters can be extracted. They have also shown that their method was robust to changes in the placement of the Kinect sensors and to environmental changes [21]. In our proposed system, we improved their work by using information from a specific part of the body, instead of the entire body. We used only ankle joint on each side of the body to measure some lower gait parameters, which we needed to improve the accuracy, because this joint carries out the most required information.

We applied a simple approach to accurately extract lower body gait parameters using only ankle joint in order to measure standard foot stride parameters in each leg. The proposed system has two phases: detecting and timing. It also requires no training and works in real-time.

Evaluation results show that the proposed system is very accurate when compared to the ground-truth based FSR system, and the other previous work [21] and [56]. The study suggests that the proposed system is affordable and non-intrusive since, in a typical use-case, a Kinect can be placed in a fixed position at home.

Chapter 2
Related works

This Chapter presents a review of some methods and techniques used in human gait analysis. There are three main methods that people used for this purpose: image processing (IP), floor sensors (FS) and sensors placed on the body or Wearable Sensors (WS). Each one of these methods can be classified into various types of techniques according to which sensor is used for as we will see. A detailed Classification and comparison of existing gait analysis systems has been presented at the end of this chapter.

A. Techniques Used for Gait Analysis:

Classification of gait analysis techniques is based on the type of devices that used to measure information which can be extracted gait parameters. These techniques can be classified into three categories: techniques that based on

1) Image processing (IP).
2) Floor sensors (FS).
3) Sensors located on the body, carried by the users (wearable sensors - WS).

There are many studies that show the validity of these sensors when measuring and analyzing the different sides of the human gait. A description of some studies on the recent methods used in human gait analysis have been presented in the following sections. They are organized according to the three categories as described above.

2.1 Image Processing (IP)

In this system, several types of camera sensors are used to gather information for gait analysis. There are some methods that used to collect data for measuring the gait parameters such as pixel count to compute the number of dark or light pixels, background segmentation which extract the background of the image, or threshold filtering, that converts image into white and black. Several researchers have studied this method in order to recognize people by the way they walk. The gait recognition algorithm has been proposed for individual identification using Dynamic Static Silhouette Templates DSST [11]. Another study proposed a new multi-view gait recognition using View Transformation Model (VTM) based on Support Vector Regression (SVR) [12]. Chang et al. have investigated gender classification from human gaits using GEI (Gait Energy Image) as a discriminative feature, and achieved a good performance in real-time [13]. In addition, Arias-Enriquez et al. used the method in the medical diagnostic field by presenting a fuzzy system to identify different human gait cycle anomalies during the phase of the cycle for knee and thigh using the sagittal plane [14].

In Muramatsu et al. study, they solved proposed a gait based person authentication technique that uses a random view transformation arrangement to decrease the accuracy drop due to view changes [15]. A recent study shows promising results in gait recognition by considering changes in the subject's path [16].

Currently, one technique of IP methods has become very important which is depth measurement, also called range imaging. In this technique a number of techniques used to evaluate and get a depth image from a view point [17]. Using these techniques, important features of the image with improved and real time process became possible.

Several methods have been technologically advanced for this purpose (Figure 2.1), such as Time-of-Flight (TOF) [18], camera triangulation (stereoscopic vision), and laser range scanner methods [19]. Other studies use infrared thermography [20], and structured light [21, 22, and 56]. Four techniques of Image processing are presented as follows:

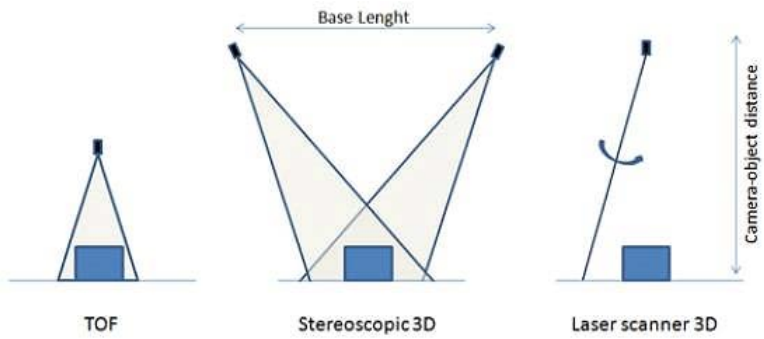


Figure 2.1: Different technology for Image Processing based system (Borrowed from [10])**.**

2.1.1 Time-of-Flight Systems (ToF)

ToF cameras based on intensity modulation deliver information about range, amplitude and intensity. The range has derived from the phase shift between the emitted and the reflected light, the amplitude values describe the amount of correlation between the two, and the intensity relates to the amount of incident active light, which itself determined by the object's distance and reflectivity. An alternative approach is based on optical shutter techniques [23] (Figure 2.2).

The observed scene is lighted with modulated near infrared light (NIL), whereby a sinusoidal modulation signal is usually used with some megahertz frequencies. Charge coupled device (CCD), complementary metal oxide semiconductor (CMOS) sensors, or a combined technology is used to receive the reflected light. Then the phase shift is measured in parallel within each pixel. This phase shift is proportional to the distance.

Time-of-flight systems for human body gait recognition have been studied by Derawi et al., They develop a biometric gait recognition system based on 3D video acquired by a Time-of-Flight sensor providing depth and intensity frames to extract gait information from the several segments and joints of the body [24]. Recently, a study by Samson et al. analyze dynamic footprint pressures with high resolution using a ToF camera [25].

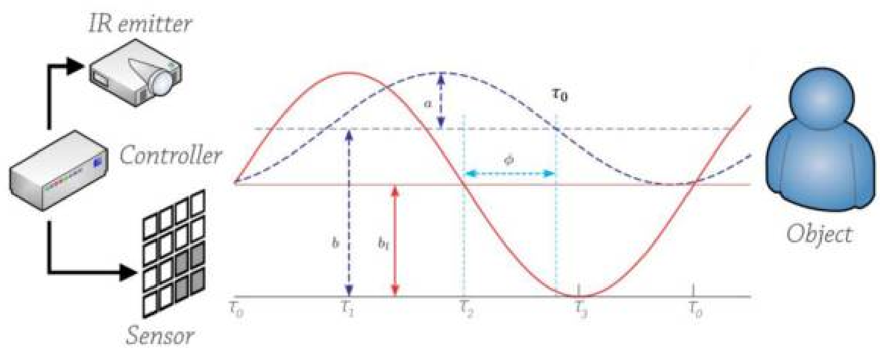


Figure 2.2: Time-of-flight working principle (Borrowed from [10]).

2.1.2 Stereoscopic Vision

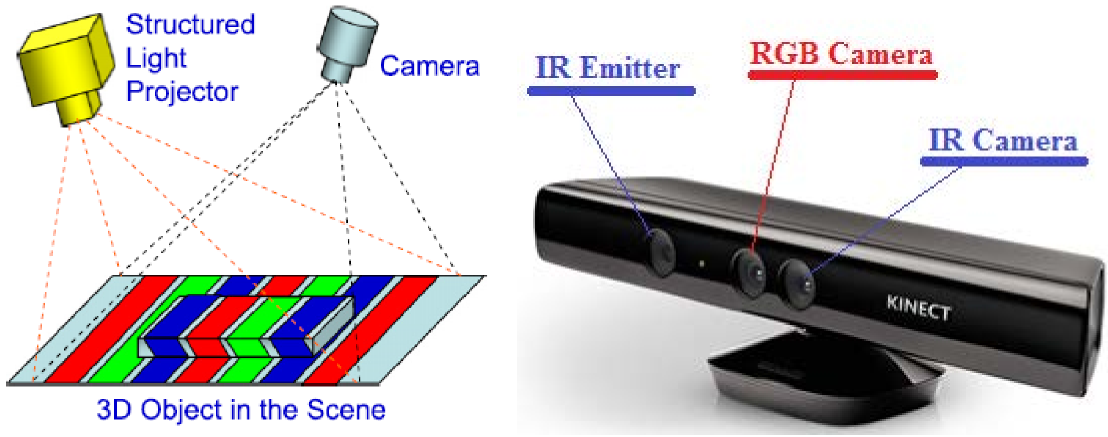
Stereoscopic vision is found in humans and many animals. Where, both eyes are in one plane, and see the same object at the same time. The brain receives two information from both eyes and combine them into one picture, taking the slight differences between each view as depth to produce 3D picture. This method can be used to determine the depth of points in the scene, for example, from the midpoint of the line between their focal points.

Computer stereo vision is a process to extract 3D information from digital images, such as produced by a CCD camera. In traditional stereo vision, two cameras, placed horizontally from each other are used to generate two different views of a scene (Figure 2.3). By comparing information from two vantage points, 3D information can be extracted by examination of the relative positions of objects in the two panels. This technique is based on the creation of a model through the calculation of similar triangles between the optical sensor, the light-emitter and the object in the scene. The technique is widely used for gait analysis. Liu et al. have represented gait using stereo gait feature, and recognized walking humans by their gait [26].

Figure 2.3: Traditional stereo vision camera.

2.1.3 Structured Light

This technique uses a projection of a special light pattern such as (grid, beam, plane, single dot, and stripes) on a body that we want to recover its 3D shape. In these methods, a 3D information is extracted by analyzing the deforming recovered projected pattern onto the scene with compare to the original one. 2D structured illumination was produced by a special light source or projector modulated by a spatial light modulator (figure 2.4 (A)) [27]. One of the most widely devices that uses this technique is Kinect sensor (Figure 2.4 (B)). Clark et al. used Kinect to create a marker based real time biofeedback system for gait retraining. Gabel et al. have calculated stride intervals and arm angular velocities using the virtual skeleton provided by Kinect sensor [21]. Another study detects heel strikes by estimating the maximum longitudinal distance between the knees which was estimated with depth images from Kinect without using a skeleton [29].



(A) **(B)**

Figure 2.4: Structured Light Technique. **(A)** Stripe indexing using colors (borrowed from [27]). **(B)** KINECT for windows Sensor.

2.1.4 Infrared Thermography (IRT)

IRT is a method of generating an images depending on temperature of the surface. The human body is a natural emitter of infrared ray and the temperature is not similar to that of the surroundings. For this characteristic, Dziuban was able to precisely estimate the infrared intensity of human body [30]. In addition, a study used this method to recognize about 78%–91% of correct human gait patterns [20] (Figure 2.5).

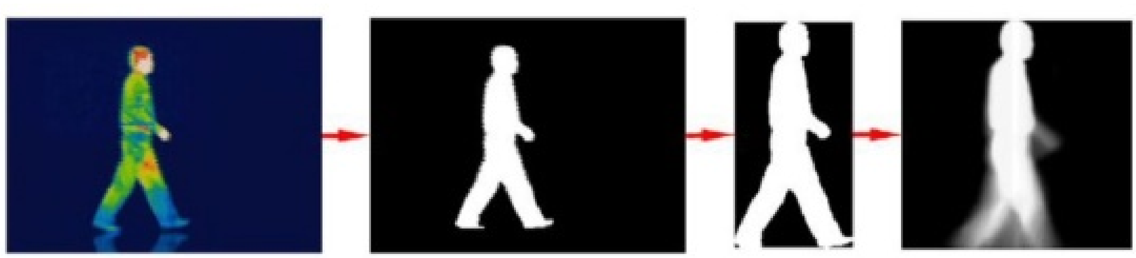


Figure 2.5: IRT image to extract the essential gait features (Borrowed from Xue *et al.* [20]).

A comparison of the four different depth measurement techniques is shown in (Table 2.1). The camera triangulation technique can be achieved using regular video cameras, but a high computational cost is required due to the stereoscopic calculation algorithms. It is obvious that ToF and Infrared Thermography techniques requires more expensive data acquisition equipment. Currently, structured light methods have been used by many people because of its low cost, sensors availability, and good accuracy to compare to other image processing methods. The accuracy values have been obtained from the literature.

Table 2.1: A comparison among different depth measurement techniques.

Method	Advantages	Disadvantages	Accuracy	Price ($)
Time of Flight	-Requires one camera only. -Real-time 3D acquisition -Less depending on scene illumination	- Low resolutions - Aliasing problem - Problem caused by reflective surface.	91% - 97% [24]	300 - 4600
Camera Triangul-ation	- Higher resolution. - No special conditions in terms of scene illumination	- High computational cost - Two cameras at least is required.	70% [26]	500 - 2300
Structured Light	- Robust and accurate measurements of random object shape with a wide range of materials - Able to get geometry and texture using same camera	- Irregular functioning with motion scenes - Superposition of the light pattern with reflections	99% [22]	200 - 240
Infrared Thermo-graphy	- Accurate reliable and fast, output - Anility to scan a large surface area in real-time - A very little skill required for monitoring	- High cost of the instrument. - If the scene is separated by glass/polythene, the system cannot detect the inside temperature. - Emissivity problems	78% - 91% [20]	1250 - 23000

2.2 Floor Sensors (FS)

Floor Sensors are a technique that the systems is based on sensors placed along the floor which is called “force platforms” or instrumented walkways. The gait is calculated while the subject is walking on force or pressure sensors and moment transducers. An example of floor sensor was built by the University of Southampton as shown in (Figure 2.6). The design of the mat is simple, by using a switch made of perpendicular wires held apart by foam, which contact when force is applied. Although this method gives an accurate result, it costs high, hard to move, and limited to lower body gait analysis only.

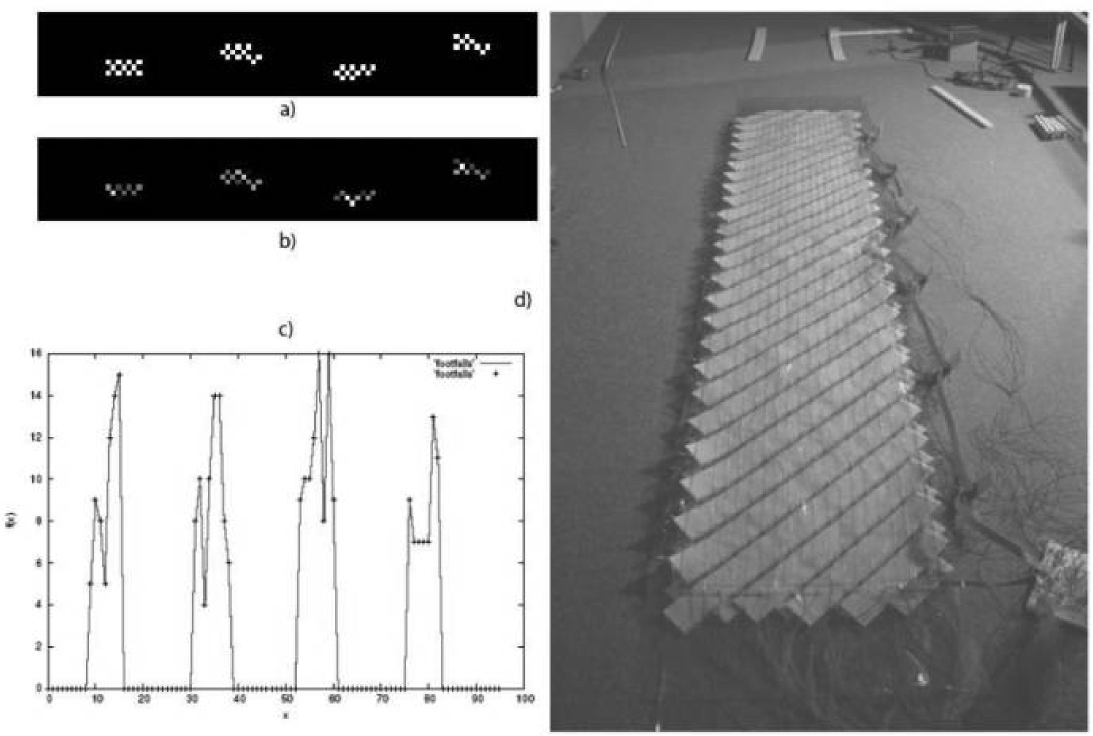


Figure 2.6: Gait analysis using floor sensors. (**a**) Steps recognized; (**b**) time elapsed in each position; (**c**) profiles for heel and toe impact; and finally (**d**) image of the prototype sensor mat on the floor. (Borrowed From University of Southampton).

The force applied to the ground when walking, known as Ground Reaction Force (GRF) is the feature that distinguishes Floor Sensor based systems from Image Processing based systems. Many gait analysis studies used this type of system [31, 32]. Vera et al. reports for the first time a comparative calculation of the spatiotemporal information found in the step signals to recognize person, which serves to simulate conditions of different potential applications such as smart homes or security access scenarios [33].

The applied pressure of the body to the ground is calculated as a percentage of weight In order to compare the patients' measurements. This is because pressure varies for the duration of stride while the foot is in touch with the ground, where the maximum pressure, which could go up to 120%–150% of the patient's weight, happens when the heel strike the ground and when the toes push off to take another stride.

In order to measure the discriminated force of each region of the foot independently over time, a complex sensor matrix systems are used, which may reach up to four sensors per cm² to give more important data on the patient's disease. For instance, a commercial force platforms is given by AMTI of Biometrics France as shown in (Figure 2.7).

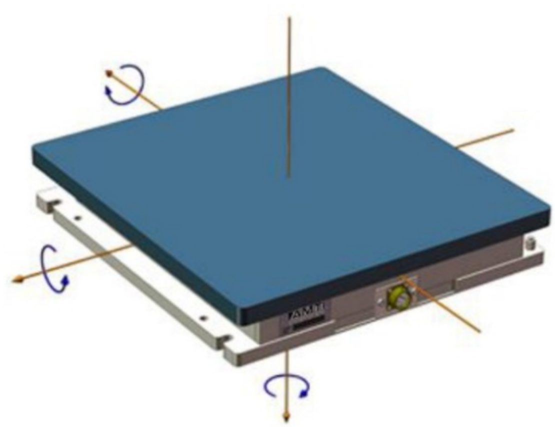


Figure 2.7: Example of AMTI series OR6-7 Force Plate showing the three forces and the three moment components along the three measurable GFR axis. (Borrowed from AMTI)

2.3 Wearable Sensors (WS)

This method of gait analysis uses wearable sensors, in which, several sensors are placed on different parts of the body, such as knees, feet or hips In order to measure some human gait parameters. This method is described in several recent reviews [34, 35].

Muro-de-la-Herran et al. have presented a comparison between the advantages and disadvantages of Non-Wearable Sensors (NWS), like IP and FS, and Wearable Sensors (WS) systems. Different factors, such as cost, power consumption, limitations, and the range of measured parameters are considered in the comparison shown in (Table 2.2) [10].

Table 2.2: Comparison between NWS and WS systems by (Muro-de-la-Herran et al. [10]).

Sys.	Advantages	Disadvantages
Non-Wearable Sensor (NWS)	- Capability to measure gait parameters simultaneously from different approaches. - Not restricted by power consumption. - Allow non-intrusive systems in terms of placing sensors on the body. - Complex analysis systems give more accurate and more calculations capacity - Enhanced reproducibility, repeatability and less external factor interfering due to controlled environment. - Real time measurement controlled by the expert.	- Because of limited walking space, the gait of the subject can be altered. - Costly equipment and experiments - Unable to monitor real life gait outdoor the instrumented setting.
Wearable Sensor (WS)	- Transparent analysis and monitoring of gait during daily activities and on the long term - Low-cost systems - Doesn't need controlled environments Allows the system to work in any place. - Increasing availability of varied reduced sensors - Wireless systems enhance usability - In clinical gait analysis, supports autonomy and active role of patients	- Due to limited battery life, the system is restricted by Power consumption. - In inertial sensors system, complex algorithms are required to measure gait parameters. - Allows analysis of limited number of gait parameters - Measurements could be affected and interfering with external uncontrolled noise

An overview of some different types of wearable sensors that are commonly used by researchers are listed below with some explanation of each type. They include force and pressure sensors, gyroscopes accelerometers, Inclinometers, goniometers, extensometers, active markers, electromyography, etc.

2.3.1 Force and Pressure Sensors

Force sensors are widely used to find the value of ground reaction force (GRF) under the foot. The sensor returns Voltage or Current proportional to applied force. Pressure sensors are used to calculate the force applied to the sensor without considering the components of this force on all coordinates. Capacitive, resistive piezoelectric and piezoresistive are the most widely used sensors of this type. There are four factors to choose the suitable sensor depending on: sensitivity, linearity, the pressure range it stands for, and the pressure range it offers:

- **Capacitive sensors:** the principle of these sensors is based on the capacity changes of the condenser that depends on different parameters, such as the distance between two electrodes.
- **Resistive sensors**: These types of sensors are based on their electrical resistance. In which the resistance decreases as the weight placed on them increases (Figure 2.8).
- **Piezoelectric sensors:** These type of sensors are consist of three deformation meters placed perpendicularly each other on a silicone gel. The applied pressure to the sensor will deform the gel and the meters compute this deformation. The overall pressure can be calculated if the gel characteristics and the deformation meter are known. The

reactivity and linearity of these sensors is excellent but because of their big size, they are not appropriate for surfaces.

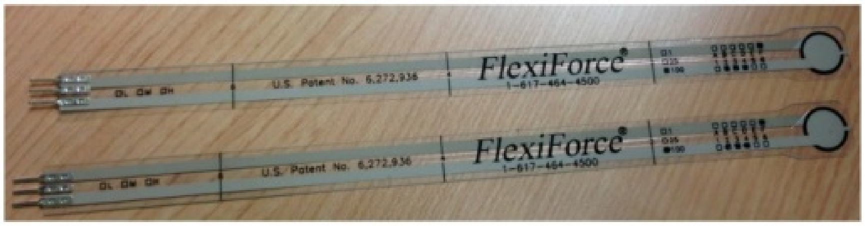


Figure 2.8: FlexiForce piezoresistive pressure sensor.

These types of sensors have been widely used by many wearable gait analysis systems in which they add them into instrumented shoes (Figure 2.9). Bae and Tomizuka have used Inertial Measurement Units (IMU) sensor in a tele-monitoring system for gait rehabilitation [36]. IMU, which has an accelerometer, a gyroscope and a magnetometer, is placed in a shoe (figure 2.10), then GRFs measured by the smart shoe and used to estimate the gait phases, foot position, stride length, and walking velocity.

Figure 2.9: Instrumented shoe from Smartxa Project: (**a**) inertial measurement unit; (**b**) flexible goniometer; and (**c**) pressure sensors which are situated inside the insole.

Figure 2.10: A tele-monitoring system for gait rehabilitation with Smart Shoes and an IMU (Borrowed from Bae et al. [36]).

Other studies use baropodometric insoles [37, 38]. In [37], it was found that an artificial neural network is able to map the relationship between insole pressure patterns and the fore-aft component of the ground reaction force. Whereas in [38] a new technique to estimate a comprehensive GRF information has been tested with pressure insoles.

Howell et al.'s study has shown that the GRF measured by the insole containing 12 capacitive sensors were highly correlated with the motion laboratory measurements, and the %RMS errors were under 10% [39]. Lincoln et al. have created another innovative system, using reflected light intensity to detect the proximity of a reflective material, and was sensitive to normal and shear loads [40].

2.3.2 Inertial Sensors

Inertial sensor is an electronic device consists of both accelerometers and gyroscopes to estimate orientation, gravitational forces, velocity, and acceleration of an object. This kind of sensors can be put inside an Inertial Measurement Unit (IMU) (figure

2.10). The accelerometer uses the basics of Newton's Motion Laws, which state that the net force applied to a body produces a proportional acceleration. We can measure the acceleration by knowing all the forces (calculated by the sensors), and object's mass.

It is possible to get the acceleration and angular velocity using 3-axis accelerometers and 3-axis gyroscopes. The velocity can be obtained by taking the integral acceleration, and we can get the position, as referring to the 3 axes, by integrating the velocity. In addition, we can get the flexion angle by integrating the angular velocity. Thus, we can find the number of steps in a specific time by analyzing the signals from the accelerometers via filtering and classifying algorithms.

Gyroscopes are based on rotational inertia (the property of an object that resists any change in rotary motion, which is motion about the axis of an object). Rotational inertia of a body can be determined by the moment of inertia. To detect changes in rotation direction, gyroscope continuously has to face the same direction as a reference.

Inertial Measurement Unit (IMU) is a type of sensor that commonly used in gait analysis. The study in [41] uses inertial sensors for quantitative gait analysis, both in-lab and in-situ; the proposed system served as a tool to facilitate the extraction of certain gait characteristics, namely symmetry and normality. Their system was evaluated against 3D kinematic measures of symmetry and normality, as well as clinical assessments of hip-replacement patients. Several systems that uses this type of sensors were found in diseases that gait disorders are a symptom such as Parkinson's [42]. Tay et al. presented a system that able to monitor the gait of Parkinson Disease patients and provide correct biofeedback which can help prevent falls, detect freezing; and from social perspective lead to better quality of life. Their system uses two integrated sensors placed on each ankle to track gait activities and a body sensor placed on the cervical vertebra to monitor body posture. This body sensor is low cost wearable wireless sensor nodes combined from a gyroscope, tri-axial accelerometer, and compass. They were able to measure parameters which might be difficult to measure manually, such as maximum acceleration of the patients during standing up, and the time it takes from sit to stand [43].

The reduction in size of inertial sensor makes it possible to put it on instrumented insoles for gait analysis, Bamberg et al. have developed Veristride insoles, which also has a special design distributed pressure sensors, Bluetooth for communication and coil for inductive recharging system (Figure 2.11).

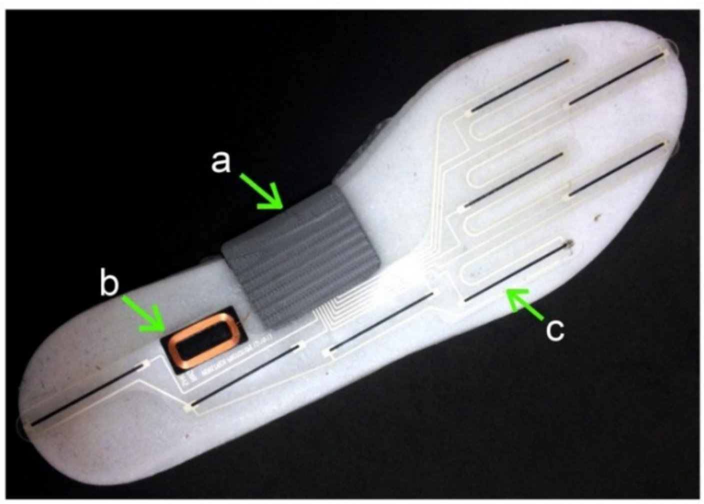


Figure 2.11: Instrumented insole: (**a**) inertial sensor, Bluetooth, microcontroller and battery module; (**b**) coil for inductive recharging; and (**c**) pressure sensors. (Borrowed from Stacy Morris Bamberg, Veristride, Salt Lake City, UT, USA).

2.3.3 Goniometers

In gait analysis, these types of sensors can be used to measure angles of ankles, knees, hips and metatarsals. Goniometers that based on strain gauge work with resistance that proportionally changes with sensor flexing (Figure 2.12). When the sensor is flexed, the material forming it stretches and the current will travel through longer path, thus its resistance increases. This resistance is proportional to the flex angle. Other types include the mechanical or inductive goniometers.

Recently, digital goniometer has been developed by Dominguez et al. it can be used for orthoses design due to its outstanding features such as high resolution, accuracy, precision, lightweight, easy donning, and easy operation [44]. These types of sensors are commonly placed in instrumented shoes to calculate ankle to foot angles [45].

Figure 2.12: Flexible Goniometer.

2.3.4 Ultrasonic Sensors

Ultrasonic sensors (also known as transceivers or transducers if they both send and receive) work like radar or sonar principles, which evaluate attributes of a target by interpreting the echoes from radio or sound waves respectively. Figure 2.13 shows active

Figure 2.13: Active Ultrasonic sensor.

ultrasonic sensors that generate high frequency sound waves and evaluate the echo which is received back by the sensor, measuring the time interval between sending the signal and receiving the echo to determine the distance to an object. Passive ultrasonic sensors are basically microphones that detect ultrasonic noise that is present under certain conditions.

Ultrasonic sensors have been used to obtain short step and stride length and the separation distance between feet, which is important data for gait analysis [46]. Huitema, et al. have calculated the swing and stance durations, and stride length using a low cost ultrasonic receiver placed on both subject's shoes, while a transmitter is placed stationary on the floor; the calculations of stance and swing durations depend on heel strike and toe off events [47].

Qi et al. present a low cost ultrasonic system that uses one transmitter and four receivers to track movement of the foot in three dimensional space. This system was able to extract a comprehensive measurements of stride parameter such as duration, length, velocity, cadence, and symmetry. Evaluation Results show that the proposed system has an average error of 2.7% for all gait parameters [48].

2.3.5 Electromyography (EMG)

Electromyography (EMG) is a method for estimating and recording the electrical activity generated by skeletal muscle contraction. Electromyograph is a device used to measure EMG, and produce a record called an electromyogram. An electromyograph detects the electrical potential generated by muscle cells when these cells are electrically or neurologically activated. The signals can be analyzed to detect medical abnormalities, activation level, or recruitment order or to analyze the biomechanics of human or animal movement.

Surface electrodes is a non-invasive method to extract the EMG signal from the subject (Figure 2.14), other invasive methods use wire or needle electrodes. Then, the calculated EMG signal is amplified, conditioned and recorded in an appropriate format for the scientific or clinical purpose. It is known that EMG signal is a complex and very small analog signal (10^{-5} to $5*10^{-3}$ Volts) which makes its measurement and recording processes hard issue.

The study of Frigo and Crenna have shown that using surface electromyography technique (SEMG) is convenient in non-invasive measurements that related to pathophysiological mechanisms, such as paresis, passive muscle-tendon, spasticity. Additionally, EMG signals are also able to measure various gait parameters. For example, the comparison of EMG plots recorded of joint angular motion and kinematic plot allows to see if one set of data able to explain the other; also, it has been shown that the EMG amplitude, obtained during gait, proportional with walking speed [49].

Recently, a study presented by Wentink et al. determined that EMG system applied to a prosthetic leg is able to predict the beginning of gait when the prosthetic leg is leading. The results was compared with inertial sensors system and found that EMG system able to predict the initial movement up to 138ms in advance of inertial sensors system [50].

Figure 2.14: Brain query Wireless EMG/EEG/ECG system.

B. Classification of existing gait analysis systems

A detailed Classification of the existing gait analysis methods of the three discussed approaches have been presented by Muro-de-la-Herran et al. [10]. The classification depends on type of methods, application, accuracy, cost and complexity of use (Table 2.3).

The results shows that the approaches that offer detailed analysis of a larger number of parameters are the Non-wearable systems (NWS) in a laboratory environment, such as marker or markerless based image processing, EMG, floor and inertial sensors. Whereas, the modern advances in wearable systems (WS) offer techniques that are cost-effective, non-intrusive which offer suitable keys for specific diagnostic requirements.

Table 2.3: Classification of existing gait analysis systems (borrowed from Muro-de-la-Herran et al. [10]).

Sys.		Technique	Application	Accuracy	Cost ($)	Ease of Use
Wearable Sensor (WS)		Inertial sensors	Segment position, Step Detection, and Stride length	Angle Coeff. Mult. Corr. > 0.96 [51] <%5 for median values Stride length error −0.8 ± 6.6 [52]	115 [10]	Complicate algorithms. Sensitive to interferences
		GRF plates	Step Detection, GRF, and Gait Phase Detection	10% of the range of GRF [40]	21,475 for one foot [10]	Bigger size than pressure sensors (less usability). Easy to analyze data
		Pressure sensors	Foot Plantar, Pressure Distribution, Gait Phase Detection, and Step Detection	Pressure correlation R > 0.95 (with clinical motion analysis laboratory measures)	18.26 [10]	Simple algorithms. Easy to put in shoe/insole. Highly nonlinear response
		EMG	Muscle Electrical Activity and Gait Phase Detection	SNR = 0.25 microvolt @ 200 Hz [Brainquiry]	37–437 [10]	Electrode setup requires a specific knowledge. Sensitive to interferences
		UWB	Step Detection and Gait Phase Detection	R = 0.96 (with ultrasound system measures) [53]	Not specified	Critical measurement condition on shoe/foot.
		Ultrasound	Step Length and Gait Phase Detection	Not Specified	25.55 [10]	Sensitive to interferences. Critical sensor situation.
		Goniometer	Joint Angles and Step Detection	R = 0.999 measures by mechanical Goniometer [44]	11.82 [10]	Setup and data analyzing is easy, but low hysteresis.
Non-Wearable Sensor (NWS)	Floor Sensor (FS)	GRF plates	Step Detection, GRF, and Gait Phase detection	±0.1% of load [AMTI]	37,500 [AMTI]	the subject have to walk on center of plate for accurate measurement
		Pressure sensor mats and platforms	Plantar Pressure Distribution, Gait Phase detection, Step Detection, and Gait Recognition	80% recognition rate [31] 2.5 to 10% EER in recognition [33] 72% step detection rate [32]	5,000–67,500 [depending on number of sensors and specifications]	Space limitations, indoor measurement, and ability of patients to make contact with the platform
	Image Processing (IP)	Single camera IP	Individual Recognition and Segment Position	77.8% recognition rate [11]	500 – 2,375 [depending on camera specs]	Simple equipment setup. Complex analysis algorithms
		Time of Flight	Segment Position, Gait Phase Detection, Foot Plantar, Pressure Distribution, and Individual Recognition	2.66%–9.25% EER recognition [24]	250– 4,625 [depending on sensor specs]	Only one camera needed Problems with reflective surfaces
		Stereoscopic Vision	Gait Phase Detection, Segment position, and Individual Recognition	70.18% recognition rate [26]	250 - 11,250 [depending on camera specs]	Complex calibration. High computational cost
		Structured Light	Segment Position and Gait Phase Detection	Correlation R=0.89 with inertial and pressure sensor measures [36] Angle measurement error = −0.8 ± 0.8° [22]	200 - 250 [depending on sensor specs]	Complex calibration. Relatively lower cost of the sensor.
		IR Thermography	Gait Phase Detection, Segment position, Individual Recognition	78%–91% recognition [20]	10K to 125K [8 camera lab. as BTS Gaitlab]	Problems related to reflectivity, absorptivity, Emissivity, transmissivity of materials.

Chapter 3
System Design

The study proposes a low-cost, non-intrusive system that can accurately measure a wide range of gait parameters using Kinect sensors and Software Development Kit (SDK). Kinect has an array of sensors, including a camera and a depth sensor. In addition to the raw depth image, Kinect extracts a 3D virtual skeleton of the body [54]. These capabilities, packed at an affordable and compact device, already led several researchers to propose its use for home monitoring and gait analysis [21], [29], [55], and [56].

We apply a simple approach to automatically and accurately extract lower body gait parameters. Specifically, we extract standard foot stride parameters using the 3D virtual skeleton. Our technique uses information from only one joint to measure stride duration and its two components: swing and stance intervals.

Empirical evaluation shows that our results are very accurate when compared to reference measurements such as those of FSR sensors, and other previous work. In addition, the proposed method is affordable and non-intrusive since, in a typical use-case, a Kinect can be placed in a fixed position at home.

3.1 Method

The study uses a technique that exploits a "virtual skeleton" produced by Kinect sensors and software (Figure 3.1). Only two joints, out of 26 joints that the skeleton frame offers, have been used in order to measure stride duration parameters. These are the ankle joints of both left and right legs.

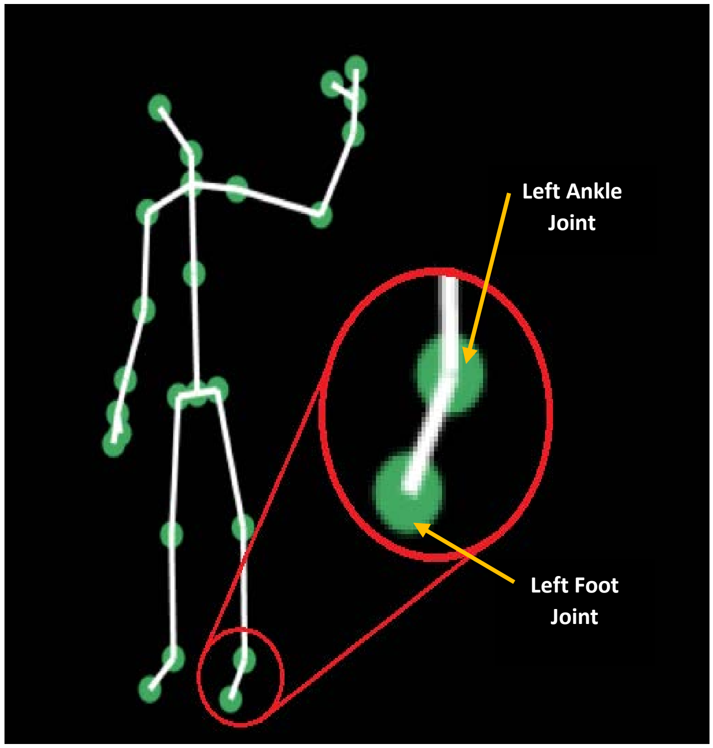


Figure 3.1: Virtual Skeleton produced by Kinect sensors and software.

In order to detect and measure stride duration and its two components: stance and swing durations, two phases have been proposed: the detection phase and the timing phase. In the “detection phase”, a difference in the horizontal position of the ankle joint between the current skeleton frame and the previous one during gait cycle is continuously calculated and compared to a predefined threshold value to see whether the foot has moved or not. The outcome of this phase is fed to another phase, the “timing phase”, to clean the signal from any random values that may have occurred during the stance state, as we will see later, and to estimate the stride duration parameters.

3.2 Subjects and Kinect Setup

The Kinect sensor was placed at an angle of 90 degrees with the middle of the path line, at a height of 50cm above the floor to capture an image of a walking subject along the path. During system setup, a subject was instructed to walk at a normal pace back and forth to choose the best threshold for the “detection phase”. The sensor used here is that of a Microsoft Kinect for Windows V2 (Figure 3.2), with the Kinect SDK v2.0 and Microsoft Visual Studio professional 2013 / C#.

Figure 3.2: Microsoft Kinect for Windows V2.

We follow the standard practice (see, for example, [2], [4], [6], and [21]) and define stride time as the time from the initial contact of one foot with the ground to the subsequent contact of the same foot with the ground (Figure 3.3). Each stride (gait cycle) is composed of a stance state, where the foot is on the ground, followed by a swing state where the foot is swung forward. The heel and toe events are fed to the “timing phase” to measure the stride duration parameters. Whenever the heel signal and/or toe signal is “pressed”, we assume that the state is STANCE. If neither signal is pressed, the state changes to SWING.

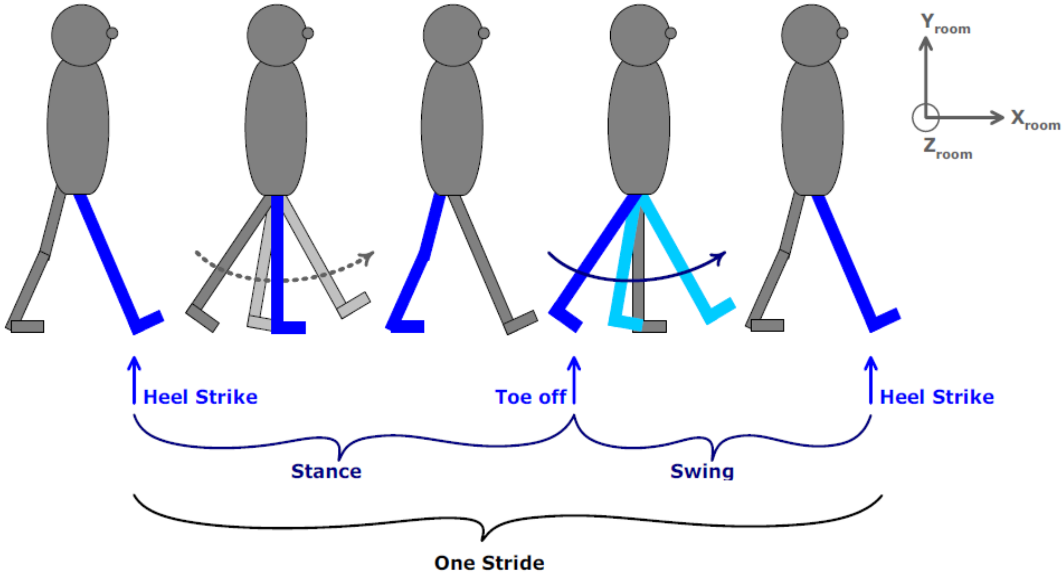


Figure 3.3: Gait cycle

3.3 Stride Detection and Partitioning (Detection Phase)

As stated previously, the Kinect sensor and its SDK provide a 3D virtual skeleton. The virtual skeleton consists of the positions of 26 joints (such as the wrists, knees, ankles, head and torso). Each joint has its own coordinate (X, Y, Z) which can be obtained from skeleton frames. Kinect provides approximately 30 skeleton frames per second. Only one joint in each leg has been used to detect gait cycle components, which is the ankle joint, since that the ankle joint coordinates are the most changing during the gait cycle (Figure 3.3). Although, the foot joint (Figure 3.1) has the same effect as the ankle joint, experimental evaluation has shown that its coordinates have more random changes than the ankle joint coordinates. The experiments have also proved that the most accurate stride, stance, and swing durations were calculated when using the ankle joint only.

The proposed technique uses the change of two coordinates of the ankle joint: the X and Z coordinates, but not the Y coordinate. The reason is that the change along the Y coordinate is so small that the Kinect sensor cannot detect during the gait cycle (Figure 3.3). Since most of the change during the gait cycle occurs along the X coordinate, the Z coordinate, in this study, is limited to finding the suitable threshold window. This threshold window plays an important role in heel strike and toe off detection.

The gait is said to be in a stance state if the toes and/or the ankle joints are touching the floor. In our proposed method, if the difference between the X-coordinates of the ankle joint at the current frame and the previous one is less than the window value, then the joint is considered in a “stance state”. Else, it is considered in a “swing state”. The purpose of using a threshold window, here, is that even if the joint doesn’t move, the difference between its coordinates at two successive frames will not equal zero, due to the limited accuracy of the Kinect sensor. The threshold window W has been calculated as follows:

$$W = \left|\frac{S}{Z}\right|$$

$Where$:
S : $Sensitivity\ of\ the\ the\ threshold\ window.$
Z : $The\ depth\ coordinate\ (distance\ from\ ankle\ joint\ to\ Kinect\ in\ meters)$.

The window “W” is reversely proportional to the “Z-coordinate” of the ankle joint because the remote subject, from Kinect sensor, produces a smaller change along the X-coordinate. The parameter “S” has been added, which can be changed manually, to give a sensitivity control over the threshold W that is suitable for the “detection phase”. During the detection phase, if we decrease “S” (“W” approaches to zero), then the state will always randomly change between the stance and swing states, even if the joint does not move due to the limited accuracy of the Kinect sensor. On the other hand, a higher “S” results in a higher “W”, and hence, the small movements of the ankle joint would not be detected, and this will reduce the accuracy of the stride duration parameters. The best way for choosing the value of “S”, for the first time only, is by tuning it until we get an acceptable result in comparison to our ground truth (FSR sensors). So, as explained earlier, if the following condition is true, we detect either a heel strike or a toe off event, then, during the “timing phase”, the stance duration is measured. Otherwise, the swing duration of the current gait cycle will be measured:

$$|X_{old} - X_{new}| < W$$

$Where$:
X_{new} : $Ankle\ joint\ X - coordinate\ of\ current\ \ skeleton\ frame$
X_{old} : $Ankle\ joint\ X - coordinate\ of\ previous\ \ skeleton\ frame$

3.4 Stride Duration Calculation (Timing Phase)

The main problem of the gait signal that come from the “detection phase” has been shown in (Figure 3.4(A)). As shown in the figure, the signal is instable during stance state due to the unpredictability of the changes in the coordinates that is produces by Kinect. This is manifested during the stance duration by the signal’s random wondering between the “stance” state and the “swing” state, although the ankle joint is fixed and within the threshold window. On the other hand, the signal, during swing duration, is quite stable because the technique applied during the detection phase considers any change of ankle position greater than the threshold window to be an indication of a swing state. One of the solutions is to increase the threshold window. But this will also reduce the accuracy of the swing and the stance durations.

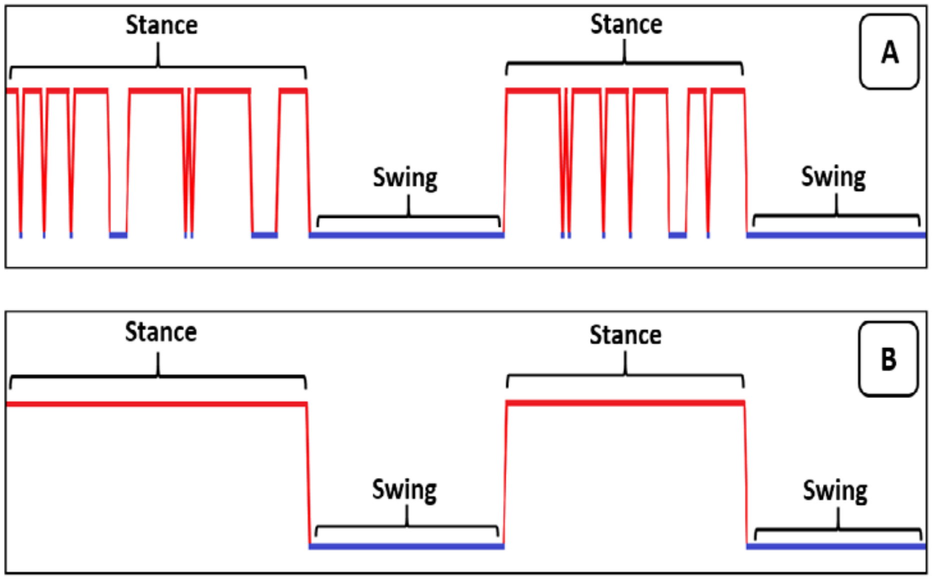


Figure 3.4: Stance duration problem and its solution. Where gait signal is captured **(A)** After detection phase and before Timing phase; **(B)** After Timing phase.

A flowchart of both of the "detection phase" and the "Timing phase" has been presented in (Figure 3.5). The way that the "detection phase" works has been discussed earlier. The "timing phase" provides a real time solution that overcomes the instability problem of the stance state and works as follows:

The stance duration is accumulated in "StAcc" from two sources: real stance timer value "StVal" itself, and the incorrect swing timer value "SwVal" (if its value is less than the swing threshold "SwThr"). Once the swing timer value "SwVal" exceeds a specific swing threshold (SwThr), the final values of the stance and the swing durations will be ready to be saved in the stance file "StFile" and the swing file "SwFile", respectively. The swing threshold value was selected to be (250 milliseconds) assuming that human beings cannot walk faster. After saving the stance and the swing durations, the value of "StAcc" is set to zero to be used again in the next gait cycle calculations, and so on. Figure (3.4 (B)) shows the signal after the "timing phase". The accuracy of the results are evaluated in the next chapter.

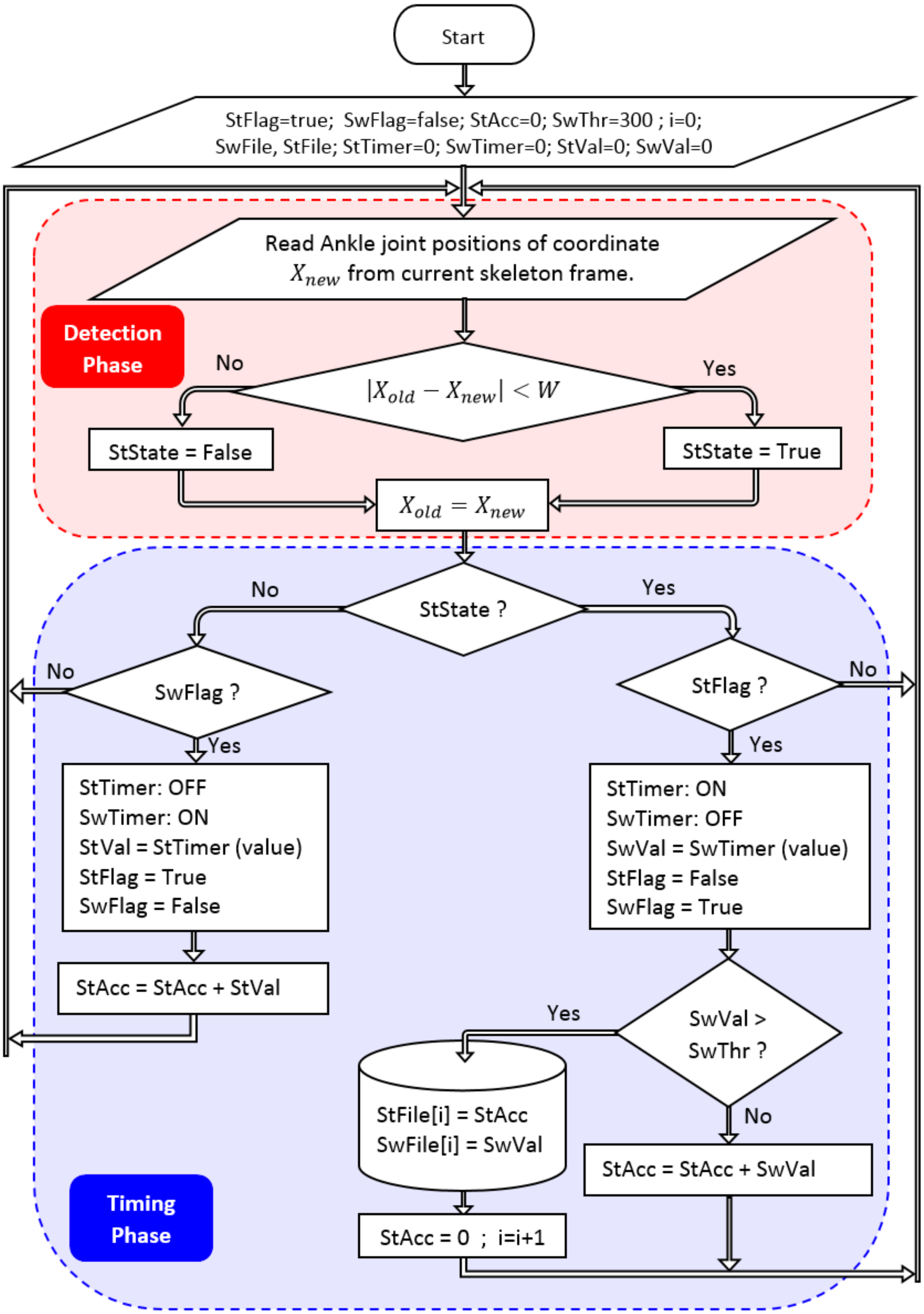


Figure 3.5: Flowchart to measure stride duration parameters: Stance and Swing duration. (A) Detection phase (shaded with red) and (B) Timing phase (shaded with blue).

Chapter 4
Evaluation Results

In this chapter stride parameter measurements have been extracted from the proposed Kinect based system. The accuracy has been compared with measurement results obtained from another system based on FSR sensors (worked as ground truth).

4.1 Validation Setup with FSR sensors

Readings from wearable sensors have been used as “ground truth” to evaluate our system accuracy. Sensor readings were sampled by custom hardware and sent to a PC via USB cable that fixed on the body using strips so it has no effect on KINECT vision. Both Kinect skeleton frames and FSR readings were synchronized and recorded at the same time.

Two Force Sensitive Resistors (FSR® 402 and FSR® 406) were placed inside insole of a sandal (Figure 4.1), so it will not affect the normal pace of walking subject. One FSR sensor (FSR® 406) was placed under the heel to capture the heel strike. The second FSR sensor (FSR® 402) was placed underneath the great toe joint to capture the time when the foot is being lifted off the ground (toe off event).

FSR sensors are based on their electrical resistance. They are used to measure the ground reaction force GRF under the foot and return a voltage, ranged between (0V ~ 5V), proportional to force applied. Recorded FSR sensor values are affected by differences in weight, foot anatomy, and shoe type. Hence, a threshold value is used such that all the reading above the threshold considered that there is a force applied to the sensor while all the reading under this threshold will be considered there is no force applied to the sensor.

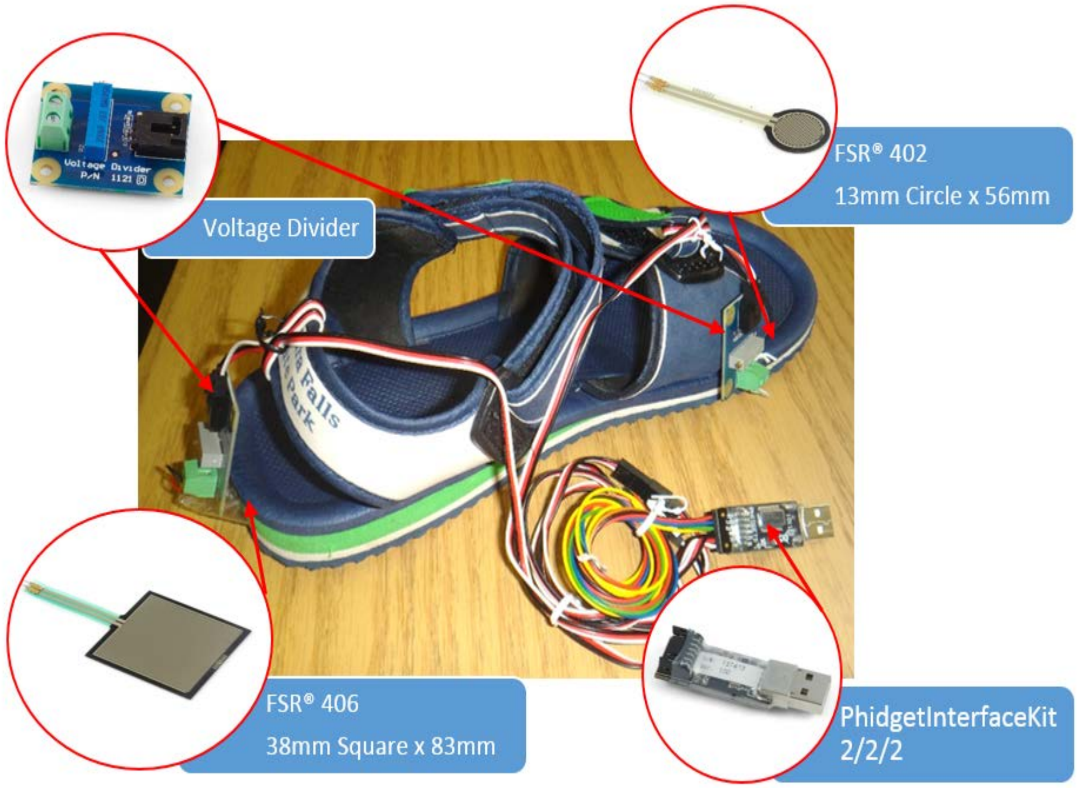


Figure 4.1: In-shoe FSR sensor.

4.2 Subject and Kinect sensor installation

Two subjects were asked to walk at a normal pace back and forth along a path line of about 3M. Kinect sensor was placed 50cm above the floor and perpendicular to the path line that beyond about 2.7M (Figure 4.2). Each subject was asked to walk 25 times along the path line for each side of the body. Hence 4 sessions have been recorded.

For each time, the subject walked 3 complete strides. First stride has been neglected because of the error that may occur due to start walking initialization, therefore; two valid strides were considered. Hence, 50 strides for each side of the subject's body have been recorded and used to measure stride duration components.

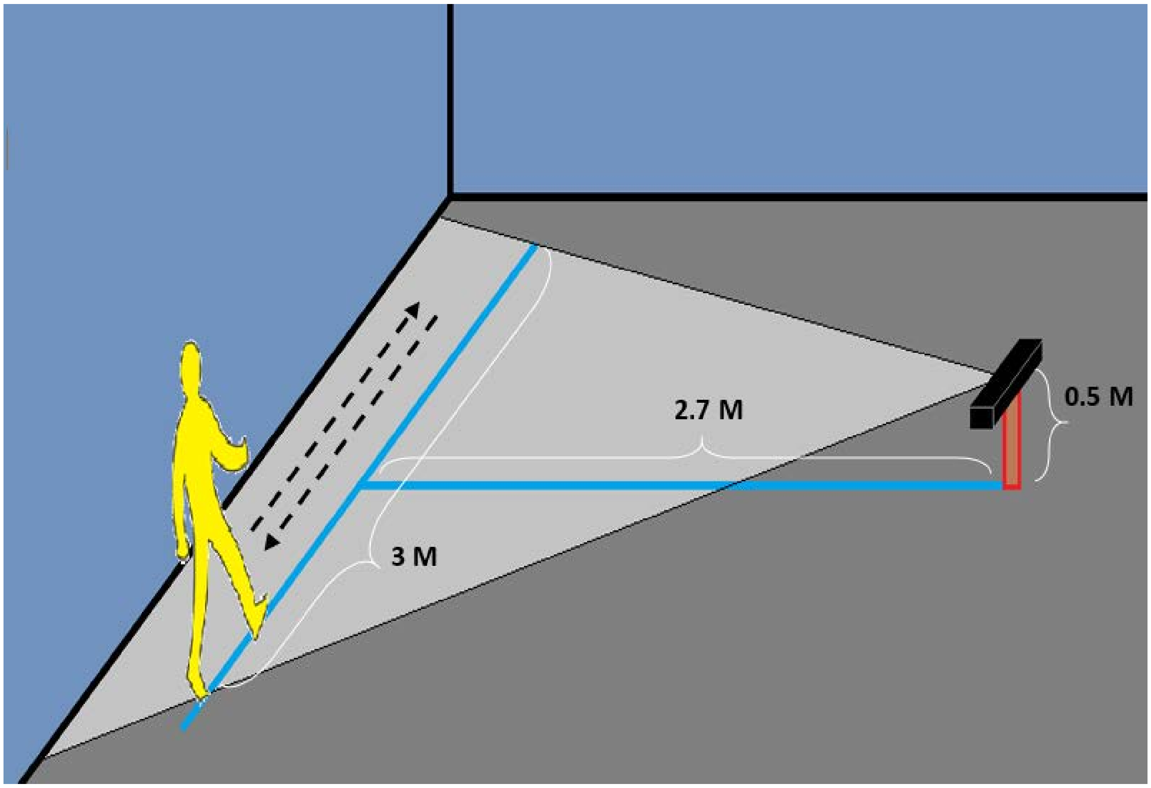


Figure 4.2: Subject and Kinect sensor installation

4.3 Evaluation Results

Evaluating the accuracy of the proposed method has been done by comparing extracted parameters from the Kinect based system with the reference values taken from FSR based system. Both systems were working simultaneously during detecting and recording each side of the subject. This will give more accurate comparison between two systems results.

The summary of the results of measuring stride durations is presented in (Table 4.1). For different components of a stride, the table shows the following statistics: (1) the average duration as measured by the pressure sensor (Avg), (2) the average difference between the duration measured by the pressure sensor and the duration measured by the Kinect sensor (Mean-diff), (3) the standard deviation between the two measurements (Std-diff), (4) the error percentage between the two measurements. The number of events is (N=50). All but the last and error columns are reported in milliseconds.

Table 4.1 shows that the results of gait parameters generated by "detection phase" followed by "Timing phase" are very accurate. The Mean-diff (or bias) is especially small (less than 1% when measuring stride duration). Both the bias and the standard-deviations in the experiment are smaller than the corresponding values reported in [21, Table I], [56, Table I].

Table 4.1: Results of Stride Duration and both Swing and Stance intervals compared to FSR sensors. The unit of measurements is a millisecond.

Interval	Subject 1				Subject 2				N
	Avg	Mean -diff	Std-diff	Error	Avg.	Mean -diff	Std-diff	Error	
Left stride	1279	4	38	0.31%	1254	7	34	0.56%	50
Right stride	1244	-3	32	0.24%	1347	2	35	0.15%	50
Left stance	819	5	53	0.61%	833	-1	41	0.12%	50
Right stance	822	-5	40	0.61%	875	-7	45	0.80%	50
Left swing	460	-1	47	0.22%	421	8	40	1.9%	50
Right swing	422	2	45	0.47%	471	9	47	1.9%	50

Chapter 5

Summary and Future Works

In this thesis, a new method has been presented for lower body gait analysis using Kinect sensor. Unlike the system proposed by [21] that uses training phase, with huge database taken from the entire body joints, our system is able to measure lower body gait parameters in real time without any training phase using information from ankle joint only.

The study proposed two phases in order to measure stride duration parameters: “Detection phase” and “Timing phase”. Using ankle joint coordinates as the input to “detection phase”, we could detect heel strike and toe off events which is required to generate a gait cycle. The "detection phase” continuously calculate the difference between x-coordinate of ankle joint taken from two successive skeleton frames of Kinect. If the difference is less than a predefined threshold, then the gait is in stance state, else, the gait is in swing state. The generated gait signal (output of “detection phase”) is fed to the “Timing phase” to extract stride parameters: stance and swing intervals, but first the gait signal is cleared from any random noise that may occur during stance state.

The study demonstrated accurate measurements of Stride duration and its two components: stance and swing intervals. A wearable sensors using FSR sensors have been used as “ground truth” to evaluate the model accuracy. The results showed that the proposed method improves the accuracy presented by [21] and [56] both in terms of having a smaller bias and in having smaller variance. The sensor used is affordable and small, thus allowing installation in domestic environments. Also, using only ankle joint to extract stride durations, comparing to entire body joints used by [21], proved that this joint has almost all required information for stride parameter measurements, and the process overhead will be much small and could be achieved in real time.

For a future works, it is necessary to use the depth (Z-coordinate) combined with the horizontal coordinate (X-coordinate) to measure stride parameters while the subject walking in curved or cyclic path instead of a straight path that proposed in our system. To do this, we will need to contribute foot ankle also. Since, the Kinect sensor will not be able to detect the coordinates of ankle joint precisely while the subject walking towards the sensor, while foot joint is still visible.

Additional important gait parameters can be added to current study such as stride length and velocity of the subject. The stride length can be found by measuring the distance between two heel strike positions. This can be done by mapping the position of the ankle joint from a pixel on the screen to its corresponding meters in the ground. The velocity of the subject can be found by dividing stride length by stride duration. Since, the current study offers stride duration. The velocity of the subject can be found in real time if we depend on current and previous ankle location.

References

[1] N.L.W. Keijsers, M.W.I.M. Horstink, and C.C.A.M. Gielen. Ambulatory motor assessment in Parkinson's disease. Movement Disorders, 21(1):34–44, 2006.

[2] J. M. Hausdorff, A. Lertratanakul, M. E. Cudkowicz, A. L. Peterson, D. Kaliton, and A. L. Goldberger. Dynamic markers of altered gait rhythm in amyotrophic lateral sclerosis. Journal of Applied Physiology, 88(6):2045–2053, 2000.

[3] D. Hodgins. The importance of measuring human gait. Med Device Technol, 19(5):42, 44–42, 47, Sep 2008.

[4] J. M. Hausdorff, D. A. Rios, and H. K. Edelberg. Gait variability and fall risk in community-living older adults: A 1-year prospective study. Archives of Physical Medicine and Rehabilitation, 82(8):1050—1056, 2001.

[5] C.-C. Yang and Y.-L. Hsu. A review of accelerometry-based wearable motion detectors for physical activity monitoring. Sensors, 10(8):7772–7788, 2010.

[6] K.J. O'Donovan, B.R. Greene, D. McGrath, R. O'Neill, A. Burns, and B. Caulfield. SHIMMER: A new tool for temporal gait analysis. In EMBC, pages 3826–3829, 2009.

[7] J. J. Kavanagh and H. B. Menz. Accelerometry: a technique for quantifying movement patterns during walking. Gait & Posture, 28(1):1–15, 2008.

[8] H.J. Luinge and P.H. Veltink. Measuring orientation of human body segments using miniature gyroscopes and accelerometers. Medical and Biological Engineering and Computing, 43(2):273–282, 2005.

[9] M. Goffredo, I. Bouchrika, J. N. Carter, and M. S. Nixon. Performance analysis for automated gait extraction and recognition in multi-camera surveillance. Multimedia Tools and Applications, 50:75–94, 2010.

[10] A. Muro-de-la-Herran, B. Garcia-Zapirain, A. Mendez-Zorrilla. Gait Analysis Methods: An Overview of Wearable and Non-Wearable Systems, Highlighting Clinical Applications. Sensors 2014, 14, 3362-3394.

[11] Y. Pratheepan, J. V. Condell, G. Prasad. The Use of Dynamic and Static Characteristics of Gait for Individual Identification. In Proceedings of 13th International Machine Vision and Image Processing Conference, Dublin, Ireland, 2–4 September 2009; pp. 111–116.

[12] W. Kusakunniran, Q. Wu, J. Zhang, H. Li. Support Vector Regression for Multi-View Gait Recognition Based on Local Motion Feature Selection. In Proceedings of 2010 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), San Francisco, CA, USA, 13–18 June 2010; pp. 974–981.

[13] P.C. Chang, M.C. Tien, J.L. Wu, C.S. Hu. Real-Time Gender Classification from Human Gait for Arbitrary View Angles. In Proceedings of 2009 11th IEEE International Symposium on Multimedia, San Diego, CA, USA, 14–16 December 2009; pp. 88−95.

[14] O. Arias-Enriquez, M.I. Chacon-Murguia, R. Sandoval-Rodriguez. Kinematic Analysis of Gait Cycle Using a Fuzzy System for Medical Diagnosis. In Proceedings of 2012 Annual Meeting of the North American Fuzzy Information Processing Society (NAFIPS), Berkeley, CA, USA, 6–8 August 2012; pp. 1–6.

[15] D. Muramatsu, A. Shiraishi, Y. Makihara, Y. Yagi. Arbitrary View Transformation Model for Gait Person Authentication. In Proceedings of 2012 IEEE 5th International Conference on Biometrics: Theory, Applications and Systems (BTAS), Arlington, VA, USA, 23–27 September 2012; pp. 85–90.

[16] Y. Iwashita, R. Kurazume, K. Ogawara. Expanding Gait Identification Methods from Straight to Curved Trajectories. In Proceedings of 2013 IEEE Workshop on Applications of Computer Vision (WACV), Tampa, FL, USA, 15–17 January 2013; pp. 193–199.

[17] R.C. Jain, R. Kasturi, B.G. Schunck. Machine Vision. McGraw-Hill: New York, NY, USA, 1995.

[18] R.R. Jensen, R.R. Paulsen, R. Larsen, Analyzing Gait Using a Time-of-Flight Camera. In Image Analysis; Salberg, A.B., Hardeberg, J.Y., Jenssen, R., Eds.; Springer: Berlin, Germany, 2009; pp. 21–30.

[19] R. Phan-Ba, S. Pierard, G. Moonen, M. van Droogenbroeck, S. Belachew. Detection and Quantification of Efficiency and Quality of Gait Impairment in Multiple Sclerosis through Foot Path Analysis. 28th Congress of the European Committee for Treatment and Research in Multiple Sclerosis 10-13th October 2012, Lyon, France

[20] Z. Xue, D. Ming, W. Song, B. Wan, S. Jin. Infrared gait recognition based on wavelet transform and support vector machine. Pattern Recognition. 2010, 43, 2904–2910.

[21] M. Gabel, R. Gilad-Bachrach, E. Renshaw, A. Schuster. Full Body Gait Analysis with Kinect. In Proceedings of 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), San Diego, CA, USA, 28 August–1 September 2012; pp. 1964–1967.

[22] R.A. Clark, Y.H. Pua, A.L. Bryant, M.A. Hunt. Validity of the Microsoft Kinect for providing lateral trunk lean feedback during gait retraining. Gait Posture 2013, 38, 1064–1066.

[23] A. Kolb, E. Barth, R. Koch, R. Larsen. Time-of-Flight Sensors in Computer Graphics. EUROGRAPHICS STAR Report, Munich, Germany, 2009.

[24] M.O. Derawi, P. Bours, K. Holien. Improved Cycle Detection for Accelerometer Based Gait Authentication. In Proceedings of 2010 Sixth International Conference on Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP), Darmstadt, Germany, 15–17 October 2010; pp. 312–317.

[25] W. Samson, A. van Hamme, S. Sanchez, L. Chèze, S. Van Sint Jan, V. Feipel. Dynamic footprint analysis by time-of-flight camera. Comput. Methods Biomech. Biomed. Engin. 2012, 15, 180–182.

[26] H. Liu, Y. Cao, Z. Wang. Automatic Gait Recognition from a Distance. In Proceedings of Control and Decision Conference (CCDC), Xuzhou, China, 26–28 May 2010; pp. 2777–2782.

[27] J. Geng. Structured-light 3D surface imaging: A tutorial. Adv. Opt. Photon. 2011, 3, 128–160.

[28] A. Leu, D. Ristic-Durrant, and A. Graser. A robust markerless vision based human gait analysis system. In SACI, pages 415–420, 2011.

[29] E. Auvinet, F. Multon, C-E Aubin, J. Meunier, M. Raison, Detection of gait cycles in treadmill walking using a Kinect, Gait and Posture (2014), http://dx.doi.org/10.1016/j.gaitpost.2014.08.006
[30] E. Dziuban, Human Body Temperature Measurement. Joint IMEKO TC-1 & XXXIV MKM Conference 2002, Wrocław, 8-12 September 2002
[31] L. Middleton, A.A. Buss, A. Bazin, M.S. Nixon. A Floor Sensor System for Gait Recognition. In Proceedings of 2005 4th IEEE Workshop on Automatic Identification Advanced Technologies, Buffalo, NY, USA, 17–18 October 2005; pp. 171–176.
[32] P. Leusmann, C. Mollering, L. Klack, K. Kasugai, M. Ziefle, B. Rumpe. Your Floor Knows Where You Are: Sensing and Acquisition of Movement Data. In Proceedings of 2011 12th IEEE International Conference on Mobile Data Management (MDM), Lulea, Sweden, 6–9 June 2011, pp. 61–66.
[33] R. Vera-Rodriguez, J. S. D. Mason, J. Fierrez, J. Ortega-Garcia. Comparative Analysis and Fusion of Spatiotemporal Information for Footstep Recognition. IEEE Transactions on Pattern Analysis & Machine Intelligence, vol.35, no. 4, pp. 823-834, April 2013, doi:10.1109/TPAMI.2012.164 (Accessed: Nov. 21, 2014 on the following link http://www.computer.org/csdl/trans/tp/2013/04/ttp2013040823-abs.html)
[34] W. Tao, T. Liu, R. Zheng, H. Feng. Gait analysis using wearable sensors. Sensors 2012, 12, 2255–2283.
[35] A.H. Abdul Razak, A. Zayegh, R.K. Begg, Y. Wahab. Foot plantar pressure measurement system: A review. Sensors 2012, 12, 9884–9912.
[36] J. Bae, M. Tomizuka. A tele-monitoring system for gait rehabilitation with an inertial measurement unit and a shoe-type ground reaction force sensor. Mechatronics 2013, 23, 646–651.
[37] H.H.C.M. Savelberg, A.L.H.D. Lange. Assessment of the horizontal, fore-aft component of the ground reaction force from insole pressure patterns by using artificial neural networks. Clin. Biomech. 1999, 14, 585–592.
[38] A. Forner Cordero, H.J.F.M. Koopman, F.C.T. van der Helm. Use of pressure insoles to calculate the complete ground reaction forces. J. Biomech. 2004, 37, 1427–1432.
[39] A.M. Howell, T. Kobayashi, H.A. Hayes, K.B. Foreman, S.J.M. Bamberg. Kinetic gait analysis using a low-cost insole. IEEE Trans. Biomed. Eng. 2013, 60, 3284–3290.
[40] L.S. Lincoln, S.J.M. Bamberg, E. Parsons, C. Salisbury, J. Wheeler. An Elastomeric Insole for 3-Axis Ground Reaction Force Measurement. In Proceedings of 2012 4th IEEE RAS EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob), Rome, Italy, 24–27 June 2012; pp. 1512–1517.
[41] A.S. Anna, N. Wickström, H. Eklund, R. Zügner, R. Tranberg. Assessment of Gait Symmetry and Gait Normality Using Inertial Sensors: In-Lab and In-Situ Evaluation. In Biomedical Engineering Systems and Technologies; J. Gabriel, J. Schier, S.V. Huffel, E. Conchon, C. Correia, A. Fred, H. Gamboa, Eds.; Springer: Berlin, Germany, 2013; pp. 239–254.
[42] A. Salarian, H. Russmann, F.J.G. Vingerhoets, C. Dehollaini, Y. Blanc, P.R. Burkhard, K. Aminian. Gait assessment in Parkinson's disease: Toward an ambulatory system for long-term monitoring. IEEE Trans. Biomed. Eng. 2004, 51, 1434–1443.

[43] A. Tay, S.C. Yen, J.Z. Li, W.W. Lee, K. Yogaprakash, C. Chung, S. Liew, B. David, W.L. Au. Real-Time Gait Monitoring for Parkinson Disease. In Proceedings of 2013 10th IEEE International Conference on Control and Automation (ICCA), Hangzhou, China, 12–14 June 2013; pp. 1796–1801.

[44] G. Dominguez, E. Cardiel, S. Arias, P. Rogeli. A Digital Goniometer Based on Encoders for Measuring Knee-Joint Position in an Orthosis. In Proceedings of 2013 World Congress on Nature and Biologically Inspired Computing (NaBIC), Fargo, ND, USA, 12–14 August 2013; pp. 1–4.

[45] S. Bamberg, A.Y. Benbasat, D.M. Scarborough, D.E. Krebs, J.A. Paradiso. Gait analysis using a shoe-integrated wireless sensor system. Trans. Inf. Tech. Biomed. 2008, 12, 413–423.

[46] Y. Wahab, N.A. Bakar. Gait Analysis Measurement for Sport Application Based on Ultrasonic System. In Proceedings of 2011 IEEE 15th International Symposium on Consumer Electronics (ISCE), Singapore, 14–17 June 2011; pp. 20–24.

[47] R.B. Huitema, A.L. Hof, K. Postema. Ultrasonic motion analysis system - measurement of temporal and spatial gait parameters. Journal of Biomechanics 35 (2002) 837–842.

[48] Y. Qi, C. Soh, E. Gunawan, K. Low, R. Thomas. Estimation of Spatial-Temporal Gait Parameters Using a Low-Cost Ultrasonic Motion Analysis System. Sensors 2014, 14, 15434-15457.

[49] C. Frigo, P. Crenna. Multichannel SEMG in clinical gait analysis: A review and state-of-the-art. Clin. Biomech. 2009, 24, 236–245.

[50] E.C. Wentink, V.G.H. Schut, E.C. Prinsen, J.S. Rietman, P.H. Veltink. Detection of the onset of gait initiation using kinematic sensors and EMG in transfemoral amputees. Gait Posture 2014, 39, 391–396.

[51] Zhang, J.T.; Novak, A.C.; Brouwer, B.; Li, Q. Concurrent validation of Xsens MVN measurement of lower limb joint angular kinematics. Physiolog. Meas. 2013, 34, N63–69.

[52] A. Salarian, P.R. Burkhard, F.J.G. Vingerhoets, B.M. Jolles, K.A. Aminian. Novel approach to reducing number of sensing units for wearable gait analysis systems. IEEE Trans. Biomed. Eng. 2013, 60, 72–77.

[53] Y. Qi, C.B. Soh, E. Gunawan, K.S. Low, A. Maskooki. Using Wearable UWB Radios to Measure Foot Clearance During Walking. In Proceedings of 2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Osaka, Japan, 3–7 July 2013; pp. 5199–5202.

[54] J. Shotton, A. Fitzgibbon, M. Cook, T. Sharp, M. Finocchio, R. Moore, A. Kipman, and A. Blake. Real-time human pose recognition in parts from single depth images. In CVPR, pages 1297–1304, 2011.

[55] E. E. Stone and M. Skubic. Evaluation of an inexpensive depth camera for passive in-home fall risk assessment. In Pervasive Health Conference, 2011.

[56] E. E. Stone and M. Skubic. Passive in-home measurement of stride-to-stride gait variability comparing vision and Kinect sensing. In EMBC, 2011.