

A Kalman filtering approach for screening of Gait datasets using a single inertial sensor placed on mid metatarsal side

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Master of Technology
in
Biomedical Engineering
by
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(Roll No.: - 220BM1135)

Based on research carried under the supervision of

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Certificate of Examination

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Supervisors' Certificate

This is to certify that the work presented in the thesis entitled *A Kalman filtering approach for screening of Gait datasets using a single inertial sensor placed on mid metatarsal side* submitted by *PRIYOBROTO BASU*, Roll Number 220BM1135, is a record of original research carried out by him under our supervision and guidance in partial fulfilment of the requirements of the degree of *Master of Technology in Biomedical Engineering*. Neither this dissertation nor any part of it has been submitted earlier for any degree or diploma to any institute or university in India or abroad.

Dr. Ravi Kant Avvari
(Supervisor)

Declaration of Originality

I, *PRIYOBROTO BASU*, Roll Number *220BM1135* hereby declare that this thesis entitled *A Kalman filtering approach for screening of Gait datasets using a single inertial sensor placed on mid metatarsal side* presents my original work carried out as a post graduate student of NIT Rourkela and, to the best of my knowledge, contains no material previously published or written by another person, nor any material presented by me for the award of any degree or diploma of NIT Rourkela or any other institution. Any contribution made to this research by others, with whom I have worked at NIT Rourkela or elsewhere, is explicitly acknowledged in the dissertation. Works of other authors cited in this dissertation have been duly acknowledged under the sections “Reference” or “Bibliography”. I have also submitted my original research records to the scrutiny committee for evaluation of my thesis.

I am fully aware that in case of any non-compliance detected in future, the Senate of NIT Rourkela may withdraw the degree awarded to me on the basis of the present dissertation.

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Priyobroto Basu

Abstract

According to the statistics provided by Centre for Disease Control and Prevention (CDC) elderly people's death is mainly caused due to falls. A study on foot gait is immensely necessary for proper diagnosis of the disease. Each and every person have a unique gait pattern but age, height and body weight are the prime factors for changes in gait trajectory. The work included in this thesis focusses on observing the gait characteristics of healthy persons. In this research, experimentation is done on 25 healthy volunteers (having no cardiovascular disease, arthritis or any disability). A prototype consisting a accelerometer sensor and a microcontroller is placed on their foot and the acceleration data is recorded. All the volunteers were asked to perform three different styles of walking – slow, normal and fast walking on a smooth flat ground surface. The acquired data is then filtered by Kalman Filtering in MATLAB for noise removal. Further, for analysis of the data peak detection is done and time interval between the gait parameters like heel strike, toe off and mid swing is calculated. A conclusion is drawn regarding the acquired results when the research is carried on the volunteers. The swing time of the normal individuals were found to be greater than the swing time of the overweight individuals. Also, the variance in Gait parameters of normal persons is higher than overweight persons indicating more versatility of normal weighted ones over the overweight peoples.

Keywords : Gait Analysis, Accelerometer, Kalman Filtering, Peak Detection, B.M.I., datasets.

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Chapter 1

Introduction

1.1 Biomechanics of locomotion

Biomechanics is a branch of science concerning the motion of a living body, considering how muscles, bones, tendons, and ligaments work in coordination to cause a movement. It brings us the interconnection between principles of classical mechanics in solving biological problems [1]. Human biomechanics became a subject of interest to improve the performance of the body. Eventually, it enabled in establishing new methods for diagnosis and recovery through better understanding of human body [2].

1.2 Kinematics and Kinetics

Biomechanics focusses on two aspects kinematics and kinetics. Kinematics deals with the geometry and time-dependent aspects of the body without considering the forces of motion. As for example, performing exercises like jumping jacks and lunges involve motion in sagittal, frontal and transverse planes. In human kinematics movement of different body parts can be measured by applying mechanical, magnetic or inertial methods [1, 2]. Kinetics, in contrast considers the effect of forces and torques to analyze a motion. Kinetic analysis is relevant during estimation of muscle force and muscle activation of a musculoskeletal body like performing a weight-lifting exercise. Force plates, instrumented tools, electromyogram (EMG) are the notable measuring devices for muscle activation and forces[2].

1.3 Gait Analysis in Medical Field

Dysfunction in the limbs is mainly caused due to musculoskeletal problems like trauma, osteoporosis, and osteoarthritis and hence it has emerged as a pivotal study of public health. When, a person experiences pain or an injury his normal gait pattern is altered, resulting in abnormal gait or even higher health complexities.

For example :-

- Problems in the skeletal and muscular structure causing pain and discomfort and rapid changing movements
- Staying inactive for a long-time causing rise in cardiovascular diseases

Gait analysis comes into picture while solving these problems. Musculoskeletal treatment and rehabilitation are now significantly controlled with the concept of Biomechanics [3].

1.4 Gait Cycle

Gait cycle is a series of cyclic movements of the trunk and limbs causing a onward advancement of the body and centre of gravity. One Gait cycle consists of Stance phase (60%) and Swing phase (40%). A normal gait cycle consists of eight distinct phases – a) Initial Contact b) Loading Response c) Midstance d) Terminal Stance e) Pre-Swing f) Initial Swing g) Mid Swing and h) Terminal Swing. Detailed description has been given below taking reference from Figure 1 [4].

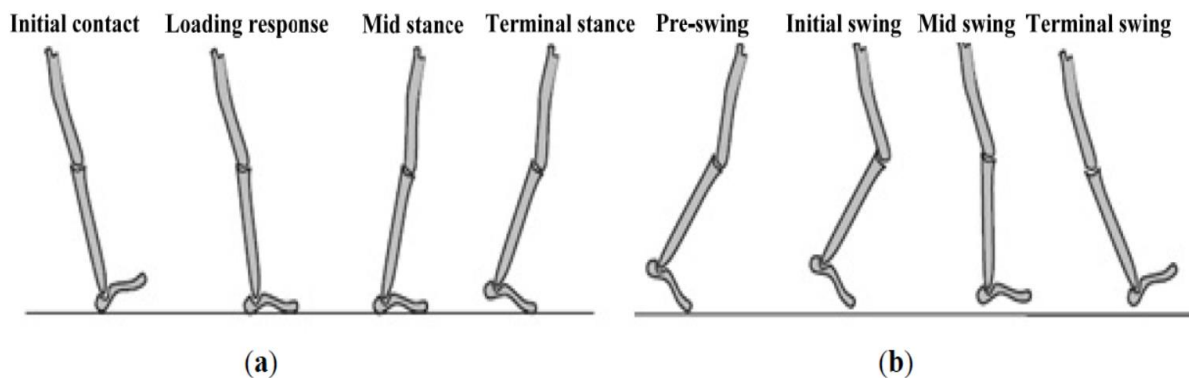


Figure 1: - Different stages of gait cycle. a) Stages of the stance phase. b) Stages of the swing phase. (Ref: Tao W. et al., “Gait Analysis Using Wearable Sensors”, Sensors 2012, 12, 2255-2283, Figure 01.)

- a) **Initial Contact** :- This parameter indicates the time point when the floor is touched by the heel also known as heel strike .

- b) **Loading Response** :- This phase occurs during which the foot lies horizontal to the floor. It begins when one foot makes initial contact and another foot is elevated for swing.
- c) **Mid-stance** :- It is the time point when the supporting extremity is crossed by the body. Mid-stance commences when the back foot is raised causing the weight of the body to be relocated to the forefoot.
- d) **Terminal Stance**:- The last phase of stance phase where the weight of the body surges ahead of the forefoot. The stance starts with the heel rising and carries on until the other foot makes contact with the ground.
- e) **Pre-Swing** :- Pre-swing set's about with the foremost proximity of the opposite limb and terminates with the toe-off.
- f) **Initial Swing**: - This time point is presumed to be 30% of the swing period, starting when the foot is lifted from the floor and ends when the stance foot and the current swinging foot are opposite.
- g) **Mid Swing**: - This phase establishes when the current limb under swing is progressing keeping the tibia vertical.
- h) **Terminal Swing**: - This is the last phase of gait cycle which starts after mid Swing and ends by floor striking of the foot.

1.5 Motion Capture System for Gait Analysis

Various technologies have been put forward for measuring human movement, examples include use of 3-D motion capture systems along with force plates, magnetic system, floor mounted systems, optoelectronic systems [5]. Detection of several points using wireless motion capture at a short range is a well-known methodology applied in medical diagnosis of foot abnormalities. In those applications mainly for detecting the finger movements the marker size must be devoid from electrical connections for normal motion [6]. Each marker is tracked by a minimum of three cameras at a time, where each camera provides a 2D view. Thus, a 3D data is reconstructed. However, due to requirement of multiple number of cameras the setup becomes suitable only for indoor purposes [7].

Using force plates along with the 3D motion capture system enables in recording the Ground Reaction Forces (GRF) [8]. But the data was restricted up to straight level walking only. Also, due to the setup being highly expensive it is affordable for some laboratories and hospitals only.

1.6 Role of Wearable Sensors in Gait Analysis

Advent of wearable sensors enabled the experimentations in diverse environments (indoor, outdoor, rough terrain). Biomedical sensors made of semiconductor and modern-day VLSI technology present a thrilling occasion for measurement of human physiological parameters in either continuous, or real-time and also nonintrusive manner [9]. These sensors are popularly known as Inertial Measurement Unit (IMU) and are an alternative to the expensive Gait analysis system [10]. IMU's mainly comprises of a tri-axial accelerometer and a tri-axial gyroscope used for measurement of linear acceleration and angular velocity respectively. The accelerometer senses the orientation by measuring the gravitational acceleration along its axes [11]. The sensor output however measures the linear accelerations also along with it and is corrupted due to the presence of Johnson-Nyquist noise and mechanical noise [12].

1.7 Wearable Sensors fused with Kalman Filter algorithms in Gait Analysis

Typically, in order to overcome the shortcomings of the sensor, the accelerometer measurements are passed through a Kalman filter to provide an accurate estimation. The Kalman filter is widely used because it can be established among all other possible linear filters, this is the only one which diminishes the covariance of the estimation error. In a notable research work, the algorithm has been able to detect the linear accelerations in the axes and the measurement noise covariances have been increased in those corresponding axes only. This ultimately lowered the Kalman gain in those axes, and preserved the important information of other axes [13].

At a certain point around the midstance period of the Gait cycle the foot lies flat on the floor and the velocity and accelerations are measured to be zero.

These zero velocity updates when incorporated in the Kalman filter tuning a precise result for position is obtained. This new algorithm is known as Zero Velocity Update (ZUPT). The effectiveness of ZUPT depends on the detection of zero velocity at stance period [14].

Gyroscopes another commonly used IMU sensor is necessary in order to detect the orientation angles from the kinematics of human leg. Since, the equations in that kinematic

model become non-linear, Extended Kalman Filtering (EKF) is utilized for drift error correction of the gyroscope. In experimental research, EKF gave an accuracy of over 97% for linear displacement [15]. The proposed EKF method proved to be more robust to ground height disturbances also [16].

Chapter 2

Literature Review

In this chapter, a scientometric analysis (VOSviewer software, version 1.6.17) have been provided (Figure 2) to map the scientific intellect related to be gait already used in the Research Journals. Searching was established using keywords like gait analysis, Inertial Measurement Unit (IMU) + Gait analysis, IMU + Parkinson's Disease, IMU + Multiple Sclerosis, IMU + Arthritis, IMU + Diabetes, IMU + Cancer. Search source included IEEE, Elsevier, ScienceDirect, and PubMed for the work published during the year 2018-2022.

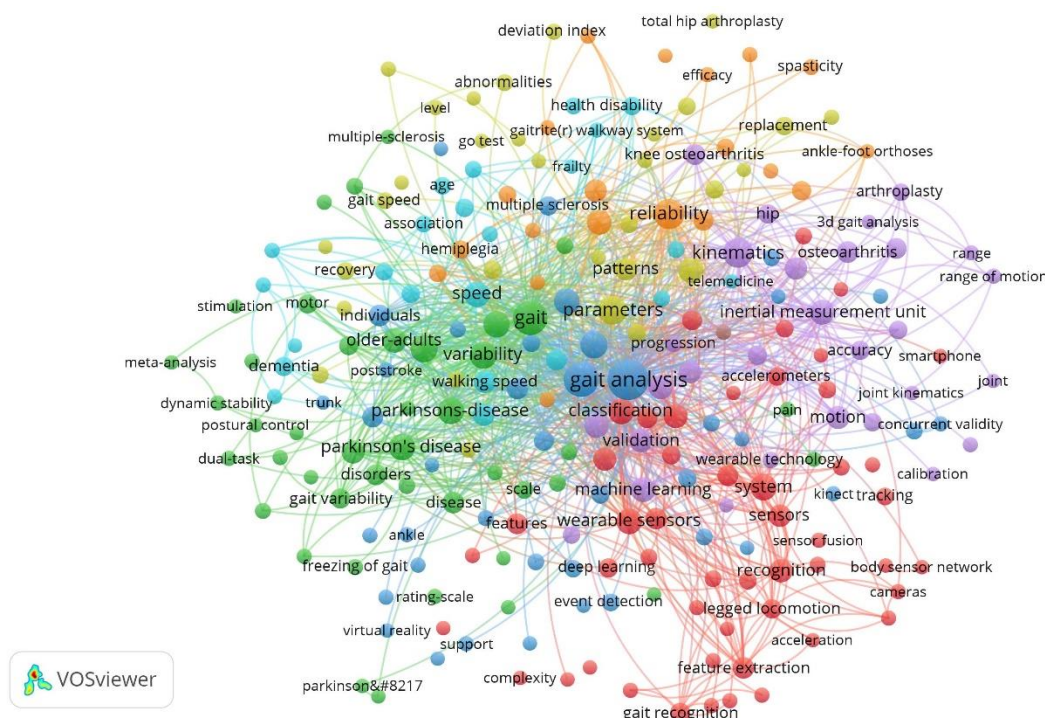


Figure 2: Scientometric analysis of search terms of relevance to medical diagnosis

According to the keywords obtained from scientometric analysis a literature has been provided in Table 1. Mainly research work is based on Spatio-Temporal parameter detection and analysis have been provided covering Parkinson's disease, Multiple Sclerosis, Arthritis, Diabetes and Cancer.

Focus have been given on the specifications of sensors used and the extent to which the research has been successful regarding giving a cure to the ailing patients.

Model	Sensor	Specification	Outcome measure	Observations
OptimEye S5 [17]	3- ϕ A, G, M	Midpoint of TV, f= 100 Hz	COD	Successful COD detection for athletes
Wireless IMMSs [18]	3- ϕ A, G, M	On knee, f=75 Hz	Hip joint angles	Hip angle detection during cycling accurate in sagittal plane but moderate in frontal and transverse plane.
SABEL Sense [19]	3- ϕ A, G, M	On forearm	Forearm shooting angle.	Variability in forearm shooting angle in netball sport detected successfully.
Hitoe Transmitter [20]	3- ϕ A	On bow, f= 25 Hz.	Postural tremors	Prediction of scores in archery by detection of postural tremors.
IMU by MTx Xsens [21]	3- ϕ A, G	On lower trunk	Lower limb joint angles	Angle detection during squat successful in sagittal plane only.
Spartan-6 series XC6SLX4 [22]	3- ϕ A	On javelin	Trajectory of Javelin throw.	Online trajectory determination in javelin throw successful.
Analog Devices [23]	3- ϕ A	On wrist and hip, f= 20 Hz	Sports activities	75-88% accuracy was observed in the identification of different sports like bike riding, exercising, football .
MotionFit SDK platform [24]	3- ϕ A	On shoe, f= 200 Hz	Real time cycling	Innovation of pedaling profile for real time cycling .
MPU 6050 [25]	3- ϕ A, G	On golf stick, f=200 Hz	Golf swing analysis	Golf swing movement and posture information visualized in 3-D.
MPU 9250	3- ϕ A,	On wrist, f=	Stroke in	Accelerometer data helpful in

[26]	G, M	50 Hz	table tennis	finding hit or miss in table tennis.
IMU sensor [27]	3-φ A, G	On elbow	Elbow angles in swimming	IMU can be used to calculate the elbow angle even in water.
Wearable IMU [28]	3-φ A, G	On sport shoes, f=200 Hz	Lateral ankle sprain hazard.	Correction system devised to provide external electrical stimulation during ankle sprain.
Xsens Awinda [29]	3-φ A, G, M	On pelvis and ankles, f= 100 Hz	Lower limb kinematics	Knee and hip joint angles were determined using IMU sensor and Extended Kalman Filtering.
Load cell [30]	A, G	As pedal tilt	Bicycling	Mechatronic rehabilitation system for individuals suffering from chronic or post-surgical conditions.
IMUs by MTws [31]	3-φ A, G	On head and chin.	head and neck strength	The repeatability and sensitivity of the head kinematics and neck strength during concussion experimentation is not high.
Head worn IMU [32]	3-φ A	On head , f=60 Hz.	Real time Gait analysis	Foot ground contact time, contact time ratio, stride time calculation possible from this work.
Xsens MTi-G-700 [33]	3-φ A, G, M	In googles	Vertical trajectory	Cascaded KF using MEMS IMU helps in determining vertical trajectory in sports.
IMU sensor [34]	3-φ A, G	On skin of the gymnasts.	IMU angles and force	High accuracy was seen during backward somersault landings.
MyoResearchÔ model 610 [35]	3-φ A, G, M	On the posterior side of	Determine acceleration and	High accuracy was seen while calculating the angles during the baseball game.

		hands, f=200 Hz.	position of pelvis, hands	
MTw, Xsens Technology [36]	3-φ A	On trunk & tibia, f= 75Hz	GRF	The work is unsuccessful and suggests segmental acceleration is not whole-body acceleration.

Table 01: Wearable sensor-based gait detection. Abbv. – A: accelerometer; G: gyroscope; M: magnetometer; TV: thoracic vertebrae ; COD: change of direction angles; GRF: Ground reaction force

Chapter 3

Motivation and Objectives of the Project

Gait is defined as “a style of walking”. The definition is further extended here to include the emergence and ambulation of human walking pattern. Obtaining an exact foot trajectory will give an assessment on the way a body moves during walking or running. Evaluating the gait features for healthy individual helps us to study the differences between a normal weighted and an overweighted one. The time interval between the peaks of the Gait parameters for different walking patterns helps in analysis of normal and overweight datasets.

The objectives which have been addressed in this thesis are as follows: -

- Obtaining the measured foot data from the accelerometer sensor.
- Performing Kalman Filtering on the measured data to get a noiseless output.
- Performing Peak Detection and finding the time intervals between the Gait parameters.
- Analyzing the time intervals for slow, normal and fast walking of different volunteers.

Chapter 4

Methodology

4.1 State of Art in Motion Sensing

The technologies involved in motion sensing are: 3-D motion capture system, Wearable Inertial Sensors, Electrogoniometers, Force Plate Mechanism, and Medical Imaging.

4.1.1 3-D Motion Capture System

Gait cycle is a series of cyclic movements of the trunk and limbs causing a forward progression of the body and centre of gravity. The gait cycle is described using spatio-temporal parameters such as stance and swing, stride length, walking speed, hip and knee angles, and ground reaction forces. A 3-D motion capture system is suitable in providing this information. A number of reflective markers are placed on the joints of the subject's body, so these can be captured by infrared cameras placed at specified distances and a trajectory is determined. The data is then processed in Visual-3D software in order to create a bone model of the lower body and generate segment-wise data. The accuracy of the measurement obtained using the calibrated camera system lies in the range of mm. In earlier times, motion capture system was regarded as benchmark in gait analysis.

4.1.2 Wearable IMU Sensors

The infrastructure required for performing gait analysis using motion capture system is expensive and requires a dedicated laboratory for its application. Recent advancements in MEMS (Micro-Electro-Mechanical system) technology have led to the development of an affordable and reliable wearable IMU (Inertial Measurement unit) system for gait analysis. There are a lot of sensors available for the study such as – accelerometer, gyroscope, and magnetometer. These sensors do not require a sophisticated laboratory and daily activities can be performed without any hindrance. Wearable sensors have helped largely in human foot trajectory detection, fall detection of elderly people, monitoring postoperative gait abnormalities and in patients suffering from various diseases like arthritis, diabetes and Parkinson's disease. These sensors are placed on distinct locations of the body such as chest wrist, foot, thigh, and shank, & are affixed using clips, belts, or other attachments.

Despite potential applications of the sensor, the inertial sensor suffers a large amount of noise and drift; hence limits the use to short time studies where the accuracy is of prime importance. To rectify the erroneous data different algorithms such as Kalman filtering, extended Kalman filtering, Zero-Order Velocity Update (ZUPT) algorithms are employed which are discussed in the section III.

4.1.3 Electrogoniometers

Electrogoniometer is an electro-mechanical device used for measuring the joint angles in gait analysis. The sensor converts the mechanical force into electrical signals. The angle measurement is possible in only one axis with accurate calibration. According to research, the electrogoniometer gives good angle measurement for elbow joint but provides poor results for knee joint.

4.1.4 Force Plate Mechanism

Force plates are employed to measure the Ground Reaction Force (GRF) of a subject during standing or its motion on the plates. It employs load cells connected at the ends of the plate to measure the induced force at all directions. Since the force plates remain fixed on the ground, the Center of Pressure (CoP) gives erroneous results during a long track movement. Moreover, footsteps precise position cannot be maintained throughout which leads to wrong calculation of CoP.

4.1.5 Medical Imaging Techniques

In medical imaging Ultrasound, X-ray, CT scan, MRI, ultrasound is commonly used to measure the geometrical structure of the human body. Such imaging modalities have been largely used for studies of relevance to injury, post-surgical observations.

4.2 Machine Learning Algorithms for Precision Measurement

The wearable IMU sensors are relatively cheaper, potable and can be performed both at indoor and outdoor settings. Typically, sensors such as tri-axial gyroscope and accelerometer are employed for the study. The angular rate of rotation is measured by gyroscope which yields orientation angles upon integration provides rotary position. Since the raw data suffers from noise and integration accumulates bias error and drifts the orientation from the true values, it limits the usability of the sensor for precision measurement. In order to reduce such errors, soft computing methods are employed such as Kalman Filter (K.F), Extended Kalman

Filter (E.K.F), Zero-Order Velocity Update (ZUPT) to provide a stable output from these sensors.

4.2.1 Kalman filter:

Filtering has become an indispensable tool in the engineering field. Normally, radio signals are distorted due to the presence of noise. An efficient filtering however eliminates this noise along with preserving the information. Similarly, use of Uninterrupted Power Supplies (U.P.S.) causes filtering of noisy line voltages and provide a smooth, fluctuation less voltage to sensitive electronic devices.

Sensors present in modern machineries helps in parameter estimation using the sensor values. As for an example, in a GPS system the measurements include providing position and velocity estimation (parameters) and the satellites signal arrival time (differential). Delivering those parameters accurately and precisely in presence of uncertainty is the major hindrance observed.

A systems dynamic model, control inputs, measurement values obtained from multiple sensors are the major parameters involved in Kalman filtering to improve the estimate of system's varying quantity (state) compared to only measurement values.

The measurement noise covariance can be dealt effectively by the Kalman filter [37, 38]. The current state update is evaluated by Kalman filtering using predicted state and sensor measurement values using the Kalman Gain factor. The Kalman Gain is calculated from covariance, which accounts for the uncertainty in predicting the system's state.

Eventually, the new state formed has better estimated uncertainty than the previous one. The process runs in a loop, adjusting the Kalman Gain according to the covariance and moving towards a better state estimate [38,39].

Kalman filtering algorithm is applicable for a linear system. The process and measurement model equations are,

$$a_t^- = Fa_{t-1}^+ + Gu_{t-1} + w_{t-1} \quad \text{----- (1)}$$

$$y_t = Ha_t + v_t \quad \text{----- (2)}$$

Where, a represents the state vector, y the measurement vector, F represents the state transition matrix, H representing observation matrix, v and w as white measurement and Gaussian process noises respectively.

The covariance matrix for process noise Q_{t-1} is depicted by:

$$Q_{t-1} = E(w_{t-1}w_{t-1}^T), \text{ where } E \text{ depicts the expectation operator.} \quad \text{--- (3)}$$

Similarly, the covariance matrix describing the measurement noise R_t is defined as

$$R_t = E(v_tv_t^T) \quad \text{----- (4)}$$

After the process model, measurement model and covariance matrices been defined as above, we can proceed with the linear Kalman filtering algorithm. The equations involved are broadly categorized in to prediction and correction blocks:

Prediction

$$\text{State Extrapolation equation} \quad \mathbf{a}_t^- = \mathbf{F}\mathbf{a}_{t-1}^+ \quad \text{----- (5)}$$

$$\text{Covariance Extrapolation equation} \quad \mathbf{P}_t^- = \mathbf{F}\mathbf{P}_{t-1}^+\mathbf{F}^T + \mathbf{Q}_{t-1} \quad \text{----- (6)}$$

Correction

$$\text{Kalman Gain} \quad \mathbf{K} = \mathbf{P}_t^- \mathbf{H}^T / (\mathbf{H} \cdot \mathbf{P}_t^- \cdot \mathbf{H}^T + \mathbf{R}_t) \quad \text{----- (7)}$$

$$\text{State Update Equation} \quad \mathbf{a}_t^+ = \mathbf{a}_t^- + \mathbf{K}(\mathbf{a}_m - \mathbf{H}\mathbf{a}_t^-) \quad \text{----- (8)}$$

$$\text{Covariance Update Equation} \quad \mathbf{P}_t^+ = (\mathbf{I} - \mathbf{K} \cdot \mathbf{H})\mathbf{P}_t^-(\mathbf{I} - \mathbf{K} \cdot \mathbf{H})^T + \mathbf{K}\mathbf{R}_t\mathbf{K}^T \quad \text{---- (9)}$$

A high Kalman Gain increases the weights of measurement values depicting the estimate graph to follow the measured output. Similarly, for a low Kalman gain, the current update state follows the predicted state. It smooths out the noise but decreases the responsiveness of the filter.

In Fig. 3, a measured accelerometer foot data taken from a male subject (Age - 26 yrs, Height – 1.69 m, Weight – 85 Kg) is given. As depicted in the figure, there is presence of a lot of noise in the output plot. Kalman Filter estimation of the measured output is produced. As depicted in the figure 4 the estimation helps in eliminating the accelerometer noise to a great extent.

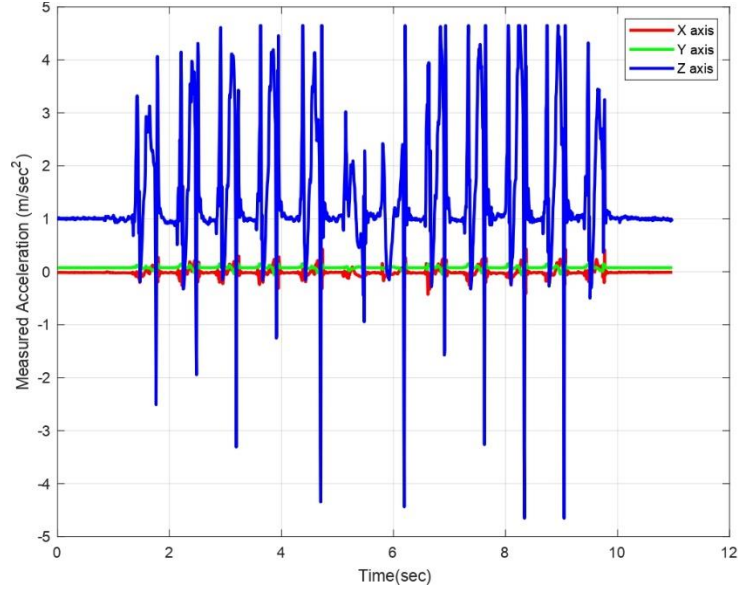


Figure 3: Measured accelerometer readings of foot trajectory

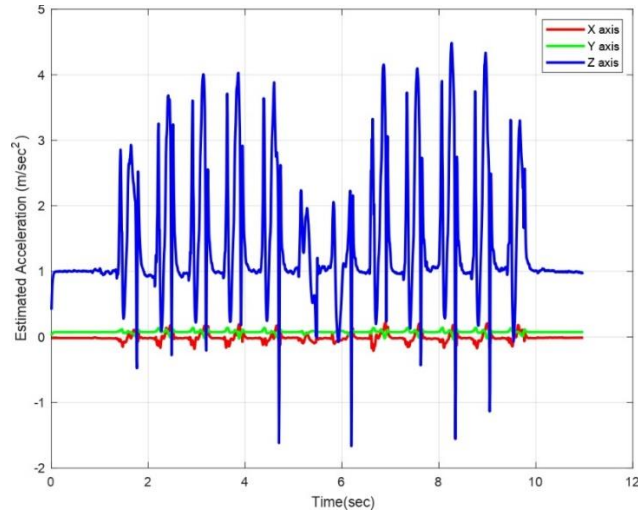


Figure 4: Estimated Accelerometer Readings of Foot Trajectory

In this foot trajectory detection Adxl345 accelerometer sensor and nano Arduino as a microcontroller have been chosen. The sensor frequency is taken at 100 Hz. Baud Rate is 230400 bits per second. Sampling frequency is 130 samples/sec.

4.2.2 Extended Kalman Filter:

Only linear transformations can be modelled using Kalman Filter :

$$a_t^- = F.a_{t-1}^+ + G.u_{t-1} + w_{t-1}$$

$$y_t = H.a_t + v_t$$

The observation that when a Gaussian random variable is linearly transformed it yields another random variable of Gaussian distribution is valid upon assuming linearity for both the state transition and measurement model of a Kalman filter. When a random variable distributed over the mean is passed through a non-linear function the resulting distribution is no longer Gaussian making Kalman filtering useless over the non-linear function domain.

Extended Kalman Filter (E.K.F) performs linear approximation of the function in non-linear form using Taylor series expansion. The non-linear function at mean is evaluated by EKF as the best approximate of the distribution. Then, a slope is estimated around that mean. First order derivative of Taylor series expansion gives us the slope as a linear value is obtained from first order derivative only.

Let's say we have the following models of state transition and measurement:

$$a_t = f(a_{t-1}, u_{t-1}) + w_{t-1}$$

$$y_t = h(a_t) + v_t$$

Where, a_t is the current state, f represents function of previous state a_{t-1} and control input u_{t-1} . h is measurement function relating the current state a_t with the measurement y_t . w_{t-1} and v_t are process and measurement noises respectively, of covariances or uncertainty Q , and R respectively.

Extended Kalman Filter Algorithm:

State Transition and Measurement matrices obtained by performing Jacobian are represented as follows -

$$F_{t-1} = \frac{\partial f}{\partial a} | (a_{t-1}^+, u_{t-1})$$

$$H_t = \frac{\partial h}{\partial a} | a_t^-$$

The E.K.F algorithm has similarity with Kalman filter algorithm:

Prediction

State Extrapolation equation

$$a_t^- = f(a_{t-1}^+, u_{t-1})$$

Covariance Extrapolation equation

$$P_t^- = F_{t-1} \cdot P_{t-1}^+ \cdot F_{t-1}^T + Q$$

Correction

Kalman Gain

$$K = P_t^- \cdot H_t^T / (R + H_t \cdot P_t^- \cdot H_t^T)$$

State Update Equation

$$a_t^+ = a_t^- + K \cdot (y_t - h \cdot a_t^-)$$

Covariance Update Equation

$$P_t^+ = (I - K.H_t). P_t^-. (I - K.H_t)^T + K.R.K^T$$

The hat “^” operator, means estimate of a variable. The superscripts “+” and “-” represent “a posteriori” and “a priori” respectively.

4.2.3 Zero- velocity (ZUPT) update:

MEMS based IMU sensors are been extensively used nowadays for estimating the trajectory of the foot. However, the large amount of drift present in the sensors should be removed beforehand. Zero-velocity update method (ZUPT) a machine learning algorithm can be used effectively for drift minimization in IMU sensors [40].

Gait cycle is a pattern of periodic, fluctuating motions of the torso & limbs which results in the center of gravity to move in forward progression. A complete gait cycle incorporates stance phase of 60% and swing phase of 40% . Five major events occur in one complete Gait cycle : Heel Strike, Foot Flat , Midstance, Push Off or Heel Off and Toe-Off . The swing phase occurs when the toe leaves the ground to the heel striking off the same leg. The stance phase extends from heel strike to midstance up to the point when any part of leg is in direct contact with the ground. For a fractional time, interval in the midstance the velocity and acceleration of the heel are exactly zero. Without applying this correction, the sensor drift increased for a few meters in four to five steps. Hence, successful elimination of drift error lies in accurately distinguishing the stance and swing phases [41].

The stance phase detection is almost a sequence matching process, where the stance phase is observed under two circumstances [40] –

- i) Acceleration should be close to g, since the x- axis and y- axis of a calibrated accelerometer are 0 and that of z- axis is nearly 9.81.
- ii) Angular velocity will be 0, since for a calibrated gyroscope all the axis are 0.

The single detection threshold method is the conventional stance detection method of ZUPT algorithm. In this method, the IMU acceleration (a_t) and angular velocities (w_t) are compared with the ZUPT acceleration threshold (σa_t) and ZUPT angular velocity threshold (σw_t) respectively [41].

A stance phase is detected when –

$$a_t \leq \sigma a_t \text{ and } w_t \leq \sigma w_t$$

Threshold gives the primary information of the entire ZUPT method. The threshold value of each activity like slow walking, fast walking, running are derived by summarizing the gait data changes from collected walking data [41].

Different experimental threshold values obtained from IMU sensors are as follows –

Normal walking range	$a_{max} - a_{min} < 3g$
Fast walking range	$3g < a_{max} - a_{min} < 4g$
Range of climbing stairs	$4g < a_{max} - a_{min} < 7g$
Range of striding/jumping	$a_{max} - a_{min} > 7g$

Where, a_{max} and a_{min} represent the magnitude of maximum acceleration and minimum acceleration respectively. g represents the gravitational acceleration. The angular threshold value (σw_t) is 0.6 rad/s. If the angular velocity (w_t) is less than 0.6 rad/s, stance phase will be represented. The disadvantage of the ZUPT algorithm is that it only utilises single threshold method for stance detection which is not an efficient way. The zero-velocity is sometimes detected prior to its occurrence; sometimes it misses to detect the phase. Due to these reasons advanced ZUPT stance detectors like double threshold method for stance detection are used nowadays [41].

4.3 Hardware Selection and Setup

4.3.1 MEMS

A MEMS (Micro electro-mechanical System) comprises of electro-mechanical components. MEMS describes the classification of micro mechatronic devices and their manufacturing processes. Devoid of any mechanical parts some MEMS get their name owing to the ability to miniaturize structures available in heavy machinery. MEMS can also be considered to be a transducer as it possesses the property of converting a signal either mechanical or optical to electrical output.

MEMS are made of embedded parts like microsensors, microprocessors, micro actuators, data processing for establishing communication. Contrasting with traditional mechatronic devices, MEMS manufacturing utilizes batch fabrication technologies similarly used for creating integrated circuits (ICs). This fabrication enables same chip embedding of both microsensors or data collectors and micro actuators or energy converters.

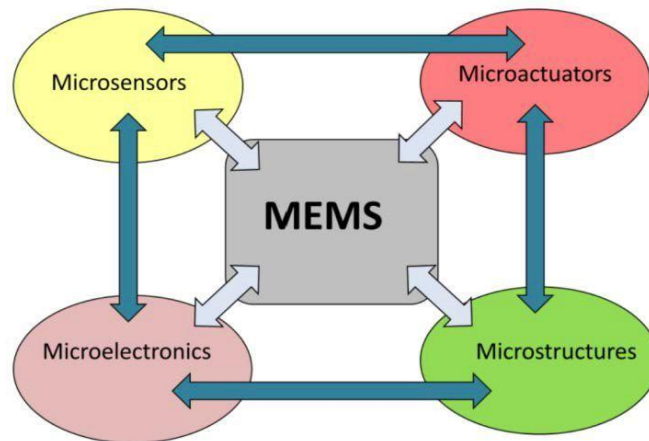


Figure 5: - MEMS technology. Courtesy

<https://berhadkarir.blogspot.com/2021/09/mems-technology-berhad-case.html>

In the following sections description on MEMS based accelerometer have been provided. To reduce the computational cost the gait analysis is done using wearable MEMS based sensors [42].

4.3.2 ACCELEROMETER

An accelerometer is used for measuring acceleration forces with respect to earth's gravity. For example, if an accelerometer stays still on a table, it gives 1g (9.8m/s^2). However, when the accelerometer free falls towards the earth it gives 0g because it is in a weightless state although its speed increases. The accelerometer comes as a simple electronic circuit. The accelerometer can be broadly classified into – a) Piezoelectric Type and b) Capacitive Type

- **Piezoelectric Type Accelerometer: -**

It is the most commonly used method where a rise in voltage is observed in the crystals due to stress, and this voltage is converted to velocity and orientation by the accelerometer.

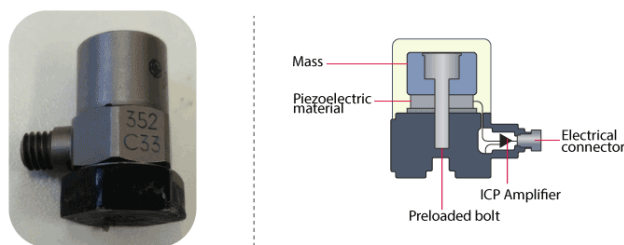


Figure 6: Piezoelectric accelerometer Courtesy

<https://byjus.com/physics/accelerometer/>

- **Capacitive Type Accelerometer: -**

The capacitance change between the microstructures is sensed by capacitive accelerometer. When acceleration causes movement in one of microstructures, the change in capacitance causes change in voltage.

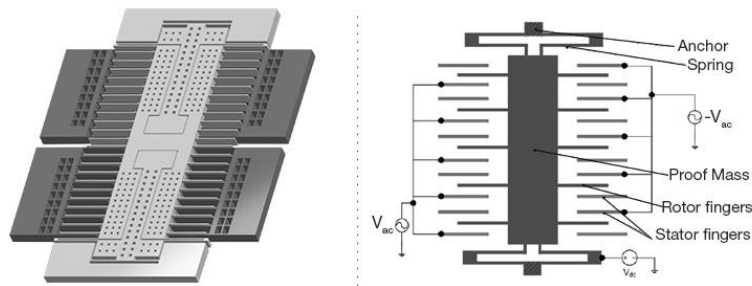


Figure 7: Capacitive accelerometer Courtesy <https://byjus.com/physics/accelerometer/>

Adxl345 has been chosen as the accelerometer for the project. This Adxl345 provide digital signals which are accessible through a digital communication protocol. No external components are required since everything is embedded in one chip. The sensor provides different configurable features for sample rate, scale and resolution.

ADXL345 is a triaxial and digital output MEMS accelerometer that is produced by Analog Devices. The sensor is very precise and of high quality. It comes with extremely good resolution and range up to $\pm 16g$ and it has been considered in diverse applications. Below are some important features of the sensor;

- Presence of the 3 axes of accelerometer on a single chip
- Minimal power consumption
- 13 bits high resolution and a range of $\pm 16g$
- Two different interrupt pins

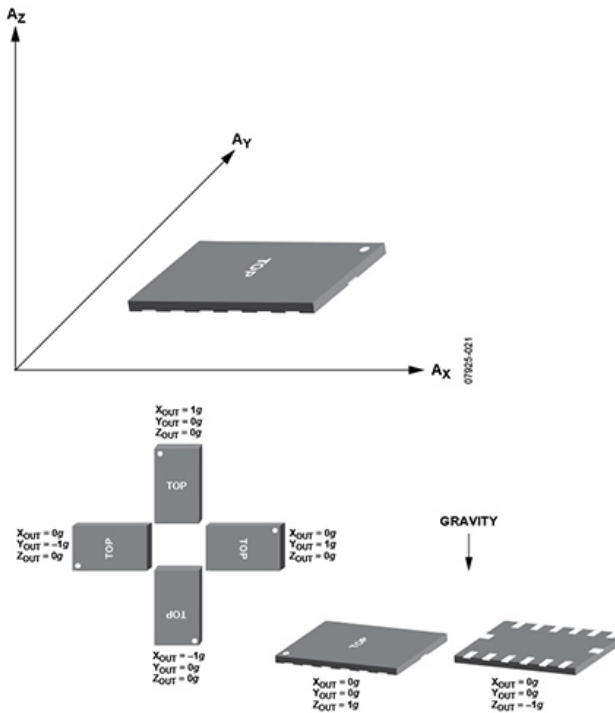


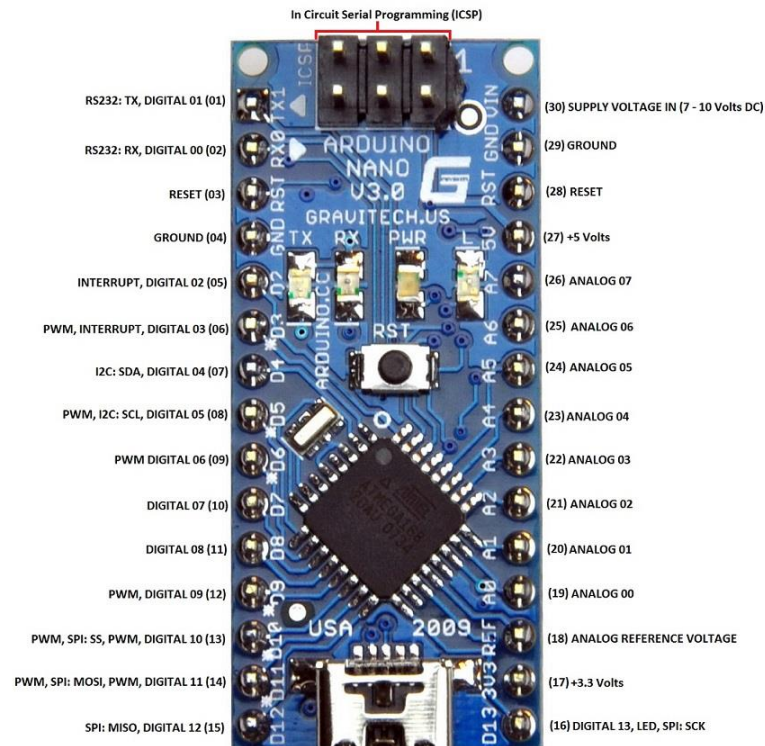
Figure 8: - ADXL345, axes of acceleration, output response. Courtesy <https://www.analog.com/media/en/technical-documentation/data-sheets/ADXL345.pdf>

4.3.3 NANO ARDUINO AS MICROCONTROLLER

Nano Arduino has been selected as a microcontroller for interfacing with Adxl345. The reasons are as follows –

- Open-source Arduino software.
- Accessible with USB communication.
- Many available digital and analog (I/O) pins.
- Serial interface pins SPI and I2C.
- PWM (pulse width modulation) pins
- Nanosized microcontroller.
- Sophisticated enough.

A pin description regarding Nano Arduino have been provided here



Arduino Nano V3 - Pin Description

www.CircuitsToday.com

Figure 9: Pin Description of Nano Arduino; Courtesy:

<https://www.circuitstoday.com/arduino-nano-tutorial-pinout-schematics>

The Adxl345 sensor is connected in SPI mode with the nano Arduino. The accelerometer is powered with 5V Vcc pin coming from Arduino. One of the three Ground pins is connected to the sensor ground pin. Chip Select (CS), Serial Data Pin (SDA), Serial Data Output (SDO) and Serial Clock (SCL) are connected with Digital Pins 10, 11, 12 and 13 respectively. The circuit diagram has been provided below -

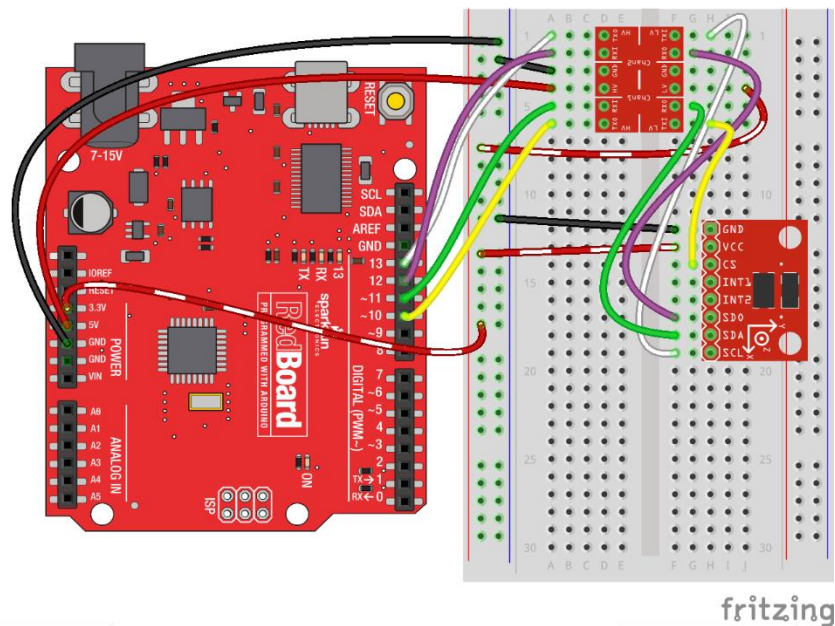


Figure 10: Arduino and Adxl345 sensor connection in SPI mode. Courtesy: <https://learn.sparkfun.com/tutorials/adxl345-hookup-guide/all>

4.4 Software Section

4.4.1 ARDUINO

Arduino platform has been used to write a major portion of the code. The code consists of essential parts which are assigned a unique task. Together, the code involves in reading the sensor values which will be utilized in later stages in MATLAB.

Below are the descriptions of some essential part of code used namely defining initial registers, data conversion, sensor frequency information, getting the output data.

4.4.1.1 REGISTER INITIALISATION

```
# include <SPI.h>                                // Adding the SPI Library
```

In the beginning of the code the library name “SPI” is included which enables to establish communication between SPI devices with the Nano Arduino as the microcontroller.

```
char POWER_CTL = 0x2D                            // Power Control Register
```

After power is supplied to Arduino, standby mode is reached by the device. Reduction of power consumption occurs and the microcontroller stays for the command of the measurement mode. Setting the measurement bit (Bit D3) in the POWER_CTL register (Address 0 x 2D) initialization of the command can still be done.

```
char BW_RATE = 0 x 2C          // Power Savings Mode
```

When power reduction is required, a low power consumption mode is present. This mechanism allows for saving of power in the data rate range 12.5 Hz to 400 Hz. To enter this mode, the LOW_POWER bit (Bit 4) is set in the BW_RATE register (Address 0 x 2C).

```
char DATA_FORMAT = 0 x 31     // SPI Connection
```

SPI bit (Bit D6) when is cleared in the DATA_FORMAT register (Address 0 x 31) 4-wire SPI mode is selected.

```
uint8_t values[6]              // Hold values read from registers
```

Six bytes would be used for 3 data (X,Y,Z) of the accelerometer.

```
int16_t x,y,z                  // Variables for storage of the values
```

16 bits of storage is allocated for each axis.

4.4.1.2 SENSOR FREQUENCY

```
SPI.transfer(0b00001010 & rate_code) // Sensor Frequency
```

The sensor frequency in SPI mode is supplied according to the rate code provided in ADXL345 datasheet. Here, rate code 1010 represents sensor frequency 100 Hz.

4.4.1.3 SERIAL PORT COMMUNICATION

```
Serial.print(x_cal, DEC)
```

```
Serial.print(y_cal, DEC)
```

```
Serial.println(z_cal, DEC)
```

The final part of the code includes sending the data in serial monitor and serial plotter. Afterwards, the data needs to be analyzed by MATLAB.

4.4.2 MATLAB

The sensor data obtained from ADXL345 is stored in an Excel sheet which will be used in MATLAB programming. Kalman filter estimation is done using those sensor values to provide a smooth and noise free output. Essential parts of programming include initialization of the state and covariance values, putting the time scale and the Kalman Filter equations.

4.4.2.1 INITIALIZING THE STATE AND COVARIANCE

```
x_hat = [0;0;0;0;0]
```

```
P = 500
```

The initial state is considered to be (n x 1) matrix where n is number of parameter dependent. Since we are unaware of the initial value of the parameters, they are considered to be 0. Since, we are guessing the state vector, the initial estimate uncertainty or covariance has also been taken a high value.

4.4.2.2 TIME SCALING

```
lz = length(numz)
```

```
fs = 130 % Number of Samples/ secs
```

```
tz = (1:lz)/fs
```

The x-axis of the output is converted to time by scaling the number of readings with sampling frequency (fs).

4.4.2.3 KALMAN FILTERING EQUATIONS

```
x_hat = F*x_hat % State Extrapolation Equation
```

```
P = F*P*F' + Q % Covariance Extrapolation Eq.
```

```
K = P*H'/(H*P*H' + R_z) % Kalman Gain
```

```
x_hat = x_hat + K*((z) - H*x_hat) % State Update Equation
```

```
P = (I - K*H)*P*(I - K*H)' + K*R_z*K' % Covariance Update Equation
```

The State Extrapolation equation ($\hat{x}$) gives a prediction of the state related to the previous estimate. The Covariance Extrapolation (P) provides uncertainty in that prediction. Both the equations serve for prediction purpose. The State Update equation ($\hat{x}$) provides the final state and the Covariance Update equation (P) gives the final corrected covariance value. The Kalman Gain (K) strikes a balance between the sensor values (z) and the estimated uncertainty (P).

4.4.2.4. PLOTTING OF RESULTS

```
figure
plot( tz, acchatz, 'r-', 'Linewidth', 2)
grid on
xlabel('Time(sec)')
ylabel('Estimated Acceleration (m/sec^2)')
legend( 'Z axis')
```

Time vs estimated acceleration plot is obtained in MATLAB for further analysis.

4.4.2.5 PEAK DETECTION

```
xt = [ 12.13 12.36 12.45 12.66 12.85 13.08 13.16 13.26 13.04 13.5 13.6 13.82 13.95
14.06];
yt = [ 3.71 4.11 2.66 1.11 3.82 4.14 3.02 1.22 1.14 1.13 3.75 3.99 2.73 1.14];
str = {'Toe Off', 'Mid-Swing', 'Heel Strike', 'Mid-Stance', 'Toe Off', 'Mid-Swing', 'Heel
Strike', 'Mid-Stance', 'Foot Flat', 'Heel Off', 'Toe Off', 'Mid Swing', 'Heel Strike', 'Foot
Flat'};
text(xt, yt, str);
```

The peaks are detected in the estimated acceleration plot and time analysis of the data reveals the gait parameters of the volunteers.

4.5 Prototype Development

4.5.1 Prototype designing and Placement of the sensor

A circuit made of Adxl345 and Nano Arduino is used for obtaining the foot acceleration data. The circuit is protected in a casing designed in AutoCAD [Fig 11 and Fig 12] and 3-D printed using Poly Lactic Acid (PLA). The above prototype is placed on the

foot using Velcro. The IMU sensors can be placed on the shank, the rearfoot or on the front foot [43] . In this research we have kept our accelerometer sensor at the front foot on the metatarsal bones [Fig 13]. The foot acceleration can be measured and analyzed afterwards.

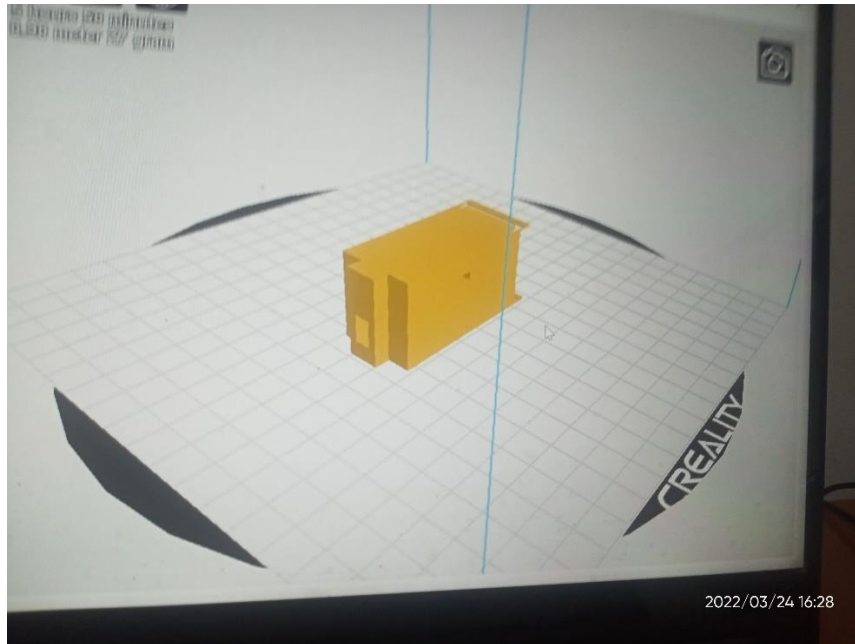


Figure 11: - AutoCAD design of the casing

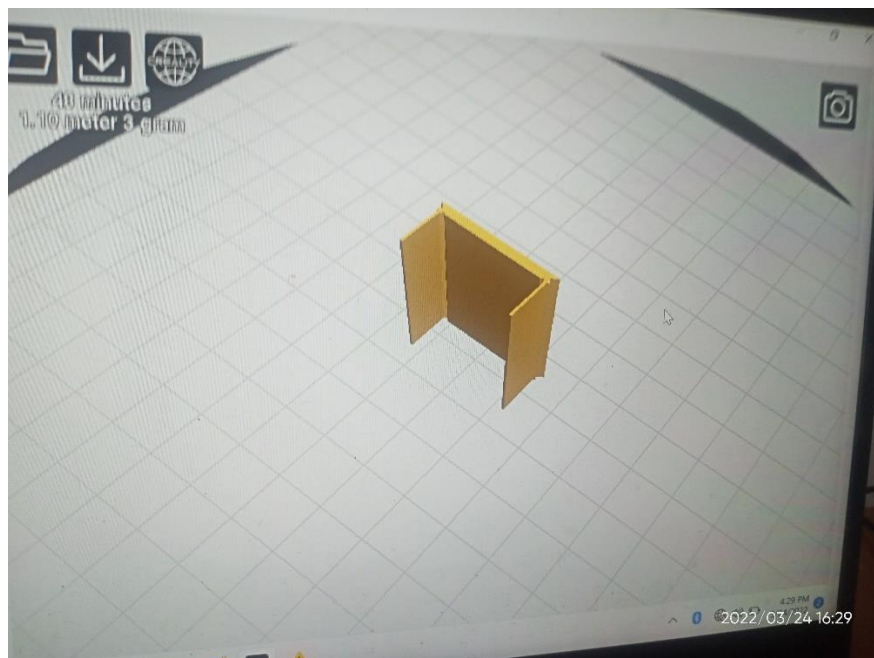


Figure 12: - AutoCAD design of the cover of the casing



Figure 13: - Placement of the IMU sensor on metatarsal bones of the foot

A study has been conducted on 25 healthy volunteers (19 male and 6 Female) who do not have any previous medical history of any cardiovascular, arthritis or any disability. Consent forms have been signed by each individual who took part in this study. All the volunteers were told to do three different walking modes – slow, normal and fast walking of at least 70 - 80 steps in each type. Their height, weight and age were recorded and B.M.I. (Body Mass Index) was calculated later. The BMI range for normal volunteers was from 19.7 – 24.1 kg/m^2 and for overweight volunteers was from 25.3-28 kg/m^2 . According to their B.M.I. all the volunteers can be classified in to Normal weighted and Over weighted individuals. The time intervals (Δt) between the peaks of Gait cycle of every subject for each style of walking were recorded. Analysis was done on that table to draw any inference.

4.5.2 Arduino and MATLAB Code

The detailed code has been provided in Appendix A and Appendix B.

Chapter 5

Results and Discussion

In this section of the thesis Kalman filter validation, measured and estimated acceleration data from Adxl345, and analysis of the datasets have been provided. The validation of Kalman filtering is done to ensure the MATLAB code works for solved Kalman Filtering equations. Then the code is tested by placing the sensor on the metatarsal bones of the foot and performing analysis of the measured signal. Finally, research on demographic data is provided.

5.1 Validation of Kalman Filter

For the validation of MATLAB code for Kalman Filtering, some previously solved examples from <https://www.kalmanfilter.net/kalman1d.html> have been taken.

5.1.1 Example – 1: Estimating the height of the building

Problem Statement:- The building height is considered to be 50m is its true height. 5m measurement error or standard deviation have been mentioned. The measurement readings are 48.54m, 47.11m, 55.01m, 55.15m, 49.89m, 40.85m, 46.72m, 50.05m, 51.27m, 49.95m.

Assumptions: - The initial state estimation or the building height is assumed 60m. The initial uncertainty or covariance error is considered to be $(15)^2 = 225$.

Solution: - The final results are plotted in MATLAB using Kalman Filtering equations (Ref. 7.2.3 and 7.2.4)

Plot: -

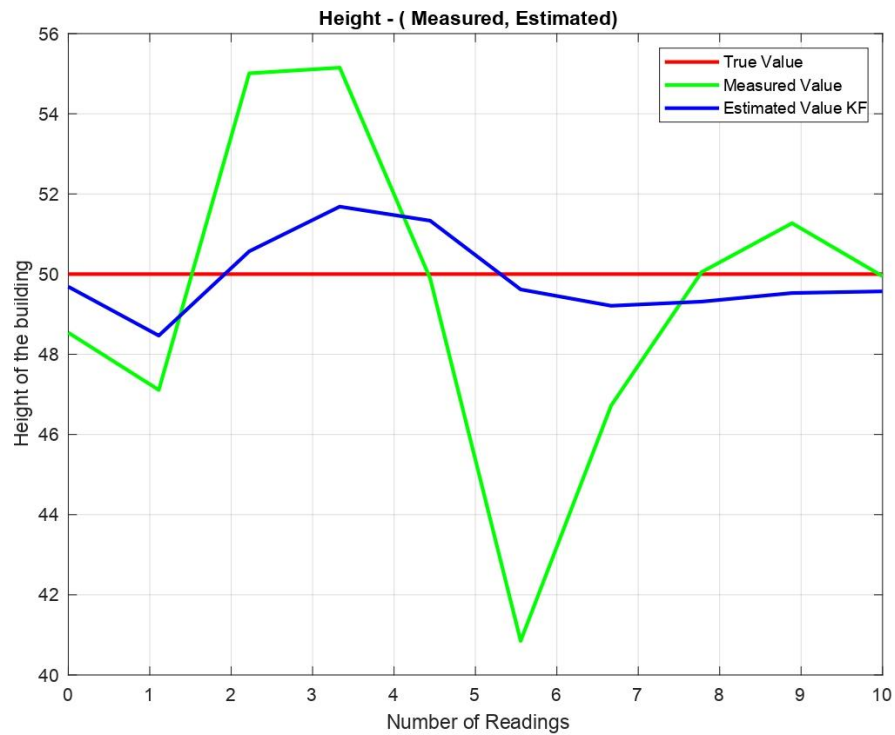


Figure 14: Kalman Filtering estimation

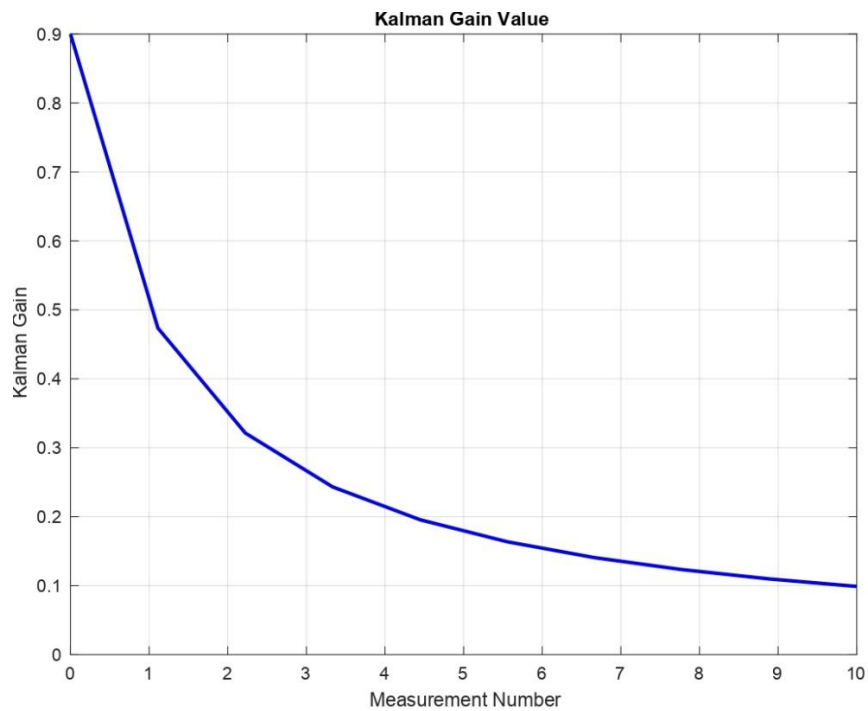


Figure 15: Kalman Gain

Conclusion :- The estimate value matches with the true value. The Kalman Gain minimizes to 0.1 which proves the code is valid.

5.1.2 Example 2: - Estimating Temperature of a Liquid in a Tank

Problem Statement :- The true temperature of the liquid is considered to be 50°C. The process noise variance (q) is taken 0.0001 considering a perfect model. The standard deviation or measurement error is 0.1°C. The temperature of the liquid considered to be true at the measuring points are: 49.979°C, 50.025°C, 50°C, 50.003°C, 49.994°C, 50.002°C, 49.999°C, 50.006°C, 49.998°C, and 49.991°C. The set of measurements is: 49.95°C, 49.967°C, 50.1°C, 50.106°C, 49.992°C, 49.819°C, 49.933°C, 50.007°C, 50.023°C, and 49.99°C.

Assumptions :- The initial state estimate or temperature is considered to be 10°C. Since, the assumption is very imperfect the initial estimate uncertainty is taken square of the error variance = $(100)^2 = 10000$.

Solution :- The final results are plotted in MATLAB using Kalman Filtering equations (Ref. 7.2.3 and 7.2.4)

Plot: -

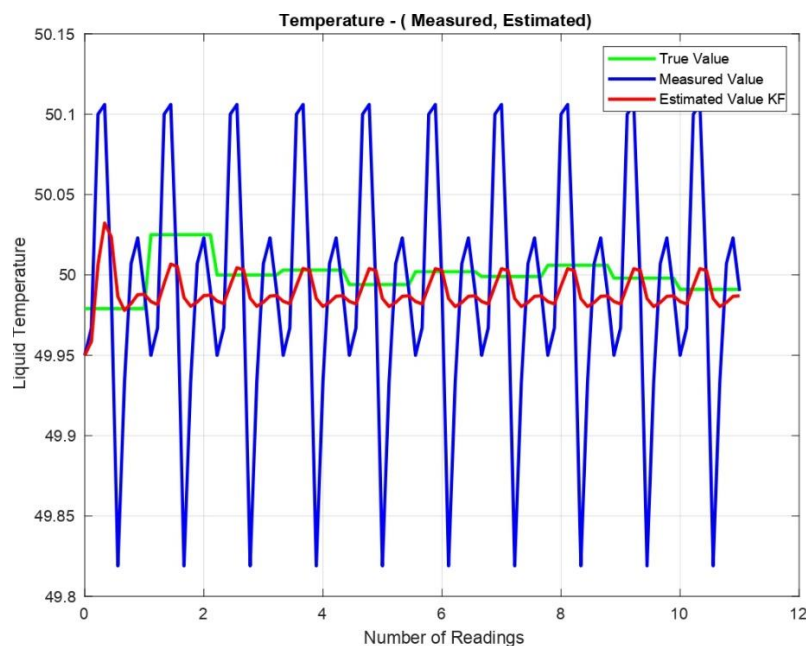


Figure 16 :- Kalman Filtering Estimation

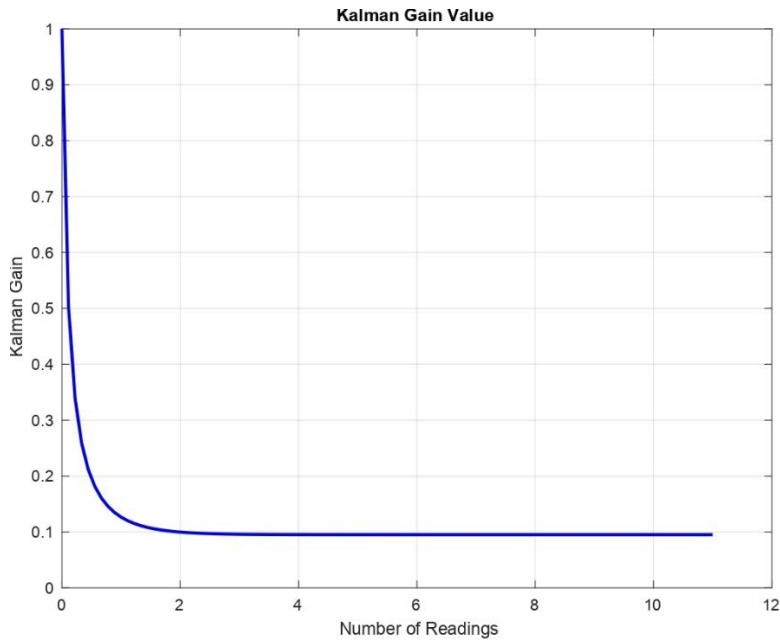


Figure 17: Kalman Gain

Conclusion :- The estimate value matches with the true value. The Kalman Gain minimizes to 0.1 which proves the code is valid.

5.1.3 Example 3: - Estimating the position of a rocket

Problem Statement :- The time period for measurement is 0.25 sec. The rocket's acceleration is taken to be 30 m/sec².

Assumptions :- The altimeter measurement error is 20m. The accelerometer measurement error is 0.1 m/sec².

Solution :- The final results are plotted in MATLAB using Kalman Filtering equations (Ref. 7.2.3 and 7.2.4)

Plot: -

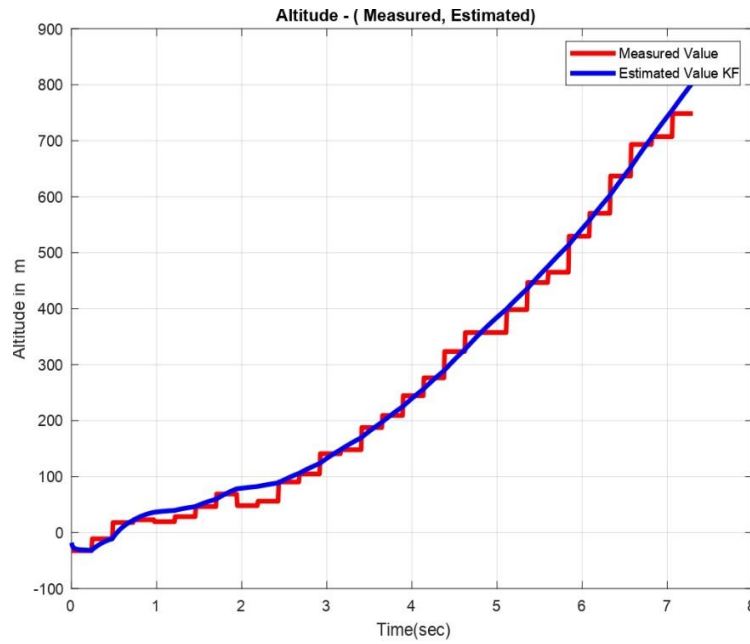


Figure 18:- Kalman Filtering Estimation

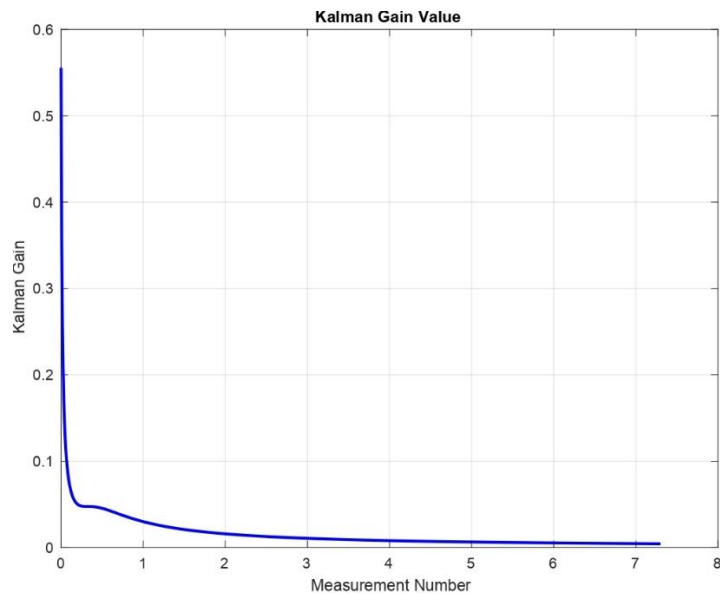


Figure 19 : - Kalman Gain

Conclusion :- The Kalman filter output matches with the measured position of the rocket. The Kalman Gain diminishes to a minimum value which indicates the covariance error has been corrected.

5.2 Obtaining the measured acceleration data from the sensor

The accelerometer (Adxl345) is connected with Nano Arduino in SPI connection. The sensor frequency is kept at 100 Hz and the sampling frequency is 130 Hz. The baud rate is chosen to be 230400 bits per second.

The real time data is recorded in Excel sheet by teraterm software. This Excel sheet data is plotted vs time in MATLAB [Fig 18]. There is negligible sideways movement so X- axis showed less prominent peaks. The test subject moved in a straight line along the Y -axis of the sensor. The up and down movement of the foot is recorded in the Z -axis of the sensor as the most prominent peaks. Each foot step taken in the signal represents a Gait cycle.

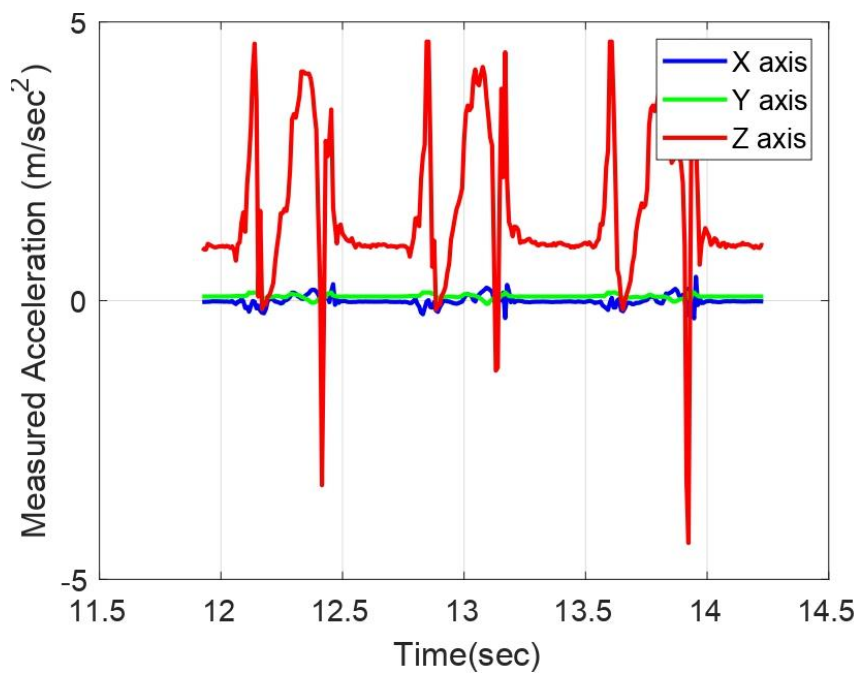


Figure 20 : - Measured Accelerometer Data of foot

The above plot will be utilized in finding the time points at which the different Gait parameters of stance phase and swing phase have occurred. However, since the sensor output [Fig 18] is noisy it is unsuitable for further analysis. Hence, the obtained plot is passed through Kalman Filtering Algorithm to smoothen out the noises.

5.3 Performing Kalman Filtering of the measured sensor data

As per discussion in article 6.2 the measured output is given to a Kalman Filter and the output is plotted vs time. For this purpose, we need to use the five Kalman Filter equations and perform MATLAB coding. A for loop is run which accepts each measured value and provides the estimated correction to it according to the Kalman Gain.

The Kalman Gain value depends on the covariance error. Greater the covariance error, lesser will be the Gain and the final estimate or correction will be nearer to the previous estimate or prediction. Similarly, lesser the covariance error, the corrected plot will follow the measured value.

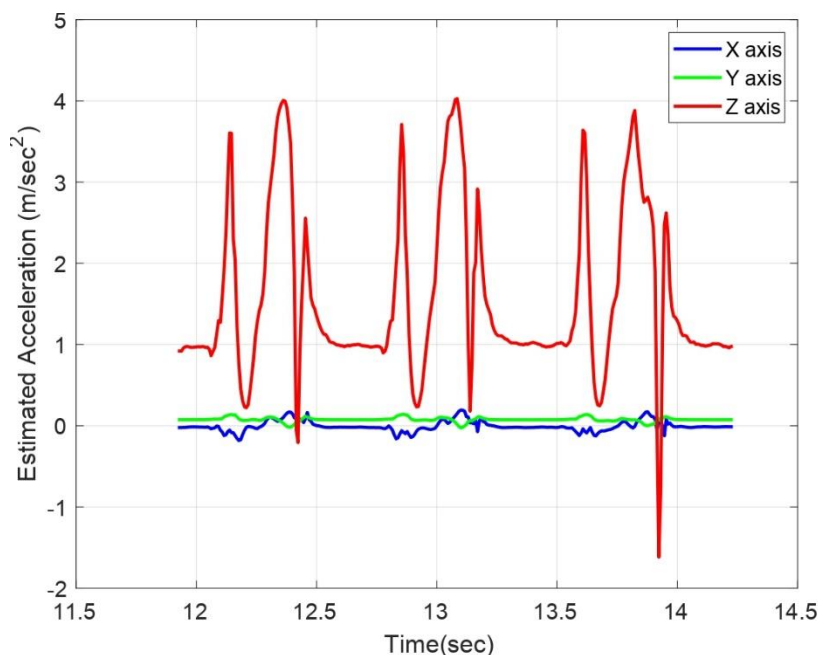


Figure 21 :- Estimated Acceleration data after Kalman Filtering

The obtained plot [Fig 19] is more noise free than measured plot [Fig 18]. This obtained plot can hence be used in finding the essential time points of Gait parameters and in peak detection. From this information we can study datasets of healthy volunteers, overweight individuals and patients suffering from Parkinson diseases etc.

5.4 Peak Detection and obtaining Time points of Gait Parameters

In a Gait cycle there is stance phase of 60% and swing phase consisting of 40%. The parameters of the stance phase comprise of Heel Strike (HL), Foot Flat (FF), Mid Stance (MST), Heel Off (HO) and Toe Off (TO). The Swing phase comprises of Initial Swing (ISW), Mid Swing (MSW) and Terminal Swing (TSW). Three peaks were notably distinguished [Fig 20] in HL, TO and MSW.

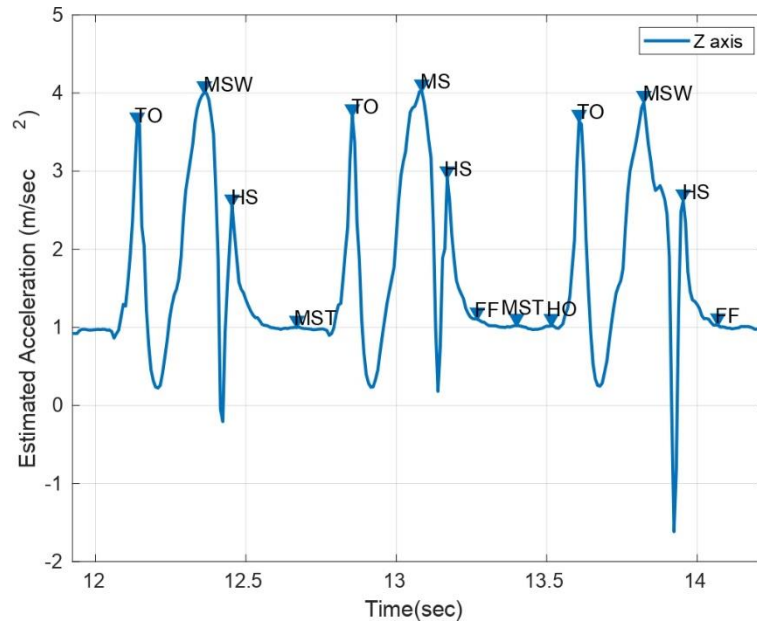


Figure 22: - Peak Detection and Gait parameters

The time interval between HS and TO, TO and SW, SW and next HS are calculated for each Gait cycle. After that, it is observed whether the time interval remains constant throughout the Gait cycle and if any inference can be drawn from it.

5.5 Data Table

A tabular data comprising of the time points of Heel Strike (HL), Toe Off (TO) and Swing (SW) along with time interval Δt between HL – TO, TO – SW and SW – HL is being displayed below (Table 2)

DEMOGRAPHIC SUBJECT DATA																	
SUBJECT_ID	AGE	GENDER	HEIGHT (cm)	WEIGHT (Kg)	BMI	STATUS	WALKING STYLE	HEEL STRIKE (HS)	TIME (SECS)					AMPLITUDE (m/sec^2)			
									TOE OFF (TO)	SWING (SW)	Δt (HS - TO)	Δt (TO - SW)	Δt (SW - HS)	HS	TO	SW	
1	26	M	169	76	26.6	Overweight	SLOW	11.22	11.91	12.15	0.69	0.24	0.27	2.75	3.59	2.84	
								12.42	13.12	13.34	0.88	0.22	0.29	2.1	3.97	2.86	
								13.63	14.31	14.55	0.68	0.24	0.28	3.41	3.74	2.83	
								14.83	15.53	15.76	0.7	0.23	0.25	2.44	3.73	2.77	
								16.01	16.73	16.95	0.72	0.22	0.22	2.34	3.83	2.89	
								17.17	17.9	18.13	0.67	0.24	0.28	2.2	3.92	2.84	
								18.41	19.08	19.3	0.67	0.22	0.24	2.36	3.92	2.9	
								19.54	20.26	20.47	0.72	0.21	0.26	2.94	3.62	2.8	
								20.73	21.41	21.64	0.68	0.23	0.26	2.71	3.51	2.87	
								21.9	22.6	22.8	0.7	0.2	0.35	3	4	2.69	
								23.15	23.75	23.98	0.6	0.23	0.68	1.94	3.77	2.83	
								24.66	24.94	25.17	0.28	0.23	0.24	3.66	3.98	3.08	
								25.41	26.07	26.31	0.66	0.24	0.25	2.17	2.94	2.66	
								26.56	27.23	27.46	0.67	0.23	0.25	2.61	3.73	2.8	
								27.71	28.39	28.65	0.68	0.26	0.28	2.49	3.65	2.86	
								28.93	29.56	29.8	0.63	0.24	0.25	2.1	3.66	2.78	
								30.05	30.72	30.97	0.67	0.25	0.23	2.71	3.74	2.9	
								31.2	31.9	32.17	0.7	0.27	0.22	2.67	4.02	2.73	
								32.39	33.1	33.34	0.71	0.24	0.26	3.39	3.96	2.6	
								33.6	34.27	34.5	0.67	0.23	0.26	3.3	3.91	3.04	
								34.76	35.45	35.73	0.69	0.28	0.22	2.75	3.61	2.79	
								35.95	36.64	36.89	0.69	0.25	0.27	3.04	3.71	2.64	
								37.16	37.8	38.04	0.64	0.24	0.24	2.27	4.01	2.71	
								38.28	38.95	39.18	0.67	0.23	0.27	2.97	4.04	2.77	
								39.45	40.12	40.37	0.67	0.25	0.26	3.29	4.01	3.73	
								40.63	41.274	41.57	0.644	0.296	0.21	3.26	3.91	2.54	
								41.78	42.45	42.7	0.67	0.25	0.27	2.93	3.89	2.95	
								42.97	43.61	43.85	0.64	0.24	0.3	2.28	4.08	2.97	
								44.15	44.74	45	0.59	0.26	0.22	2.97	3.71	2.91	
								45.22	45.87	46.11	0.65	0.24	0.25	2.77	4.03	2.77	
AVERAGE Δt									0.6644667	0.2402	0.271						
STANDARD DEVIATION Δt									0.0874855	0.01968265	0.08230934						

NORMAL	1.19	1.78	2.02	0.59	0.24	0.18	3.39	4.15	3.73
	2.2	2.79	3.02	0.59	0.23	0.17	2.95	4.35	3.58
	3.19	3.78	4.02	0.59	0.24	0.15	2.78	4.27	3.72
	4.17	4.75	4.98	0.58	0.23	0.19	2.43	4.1	3.71
	5.17	5.73	5.97	0.56	0.24	0.18	3.1	4.09	3.64
	6.15	6.71	6.97	0.56	0.26	0.19	2.48	4.02	3.98
	7.16	7.73	7.98	0.57	0.25	0.18	2.83	3.65	3.21
	8.16	8.75	8.95	0.59	0.2	0.21	3.24	3.63	3.56
	9.16	9.77	9.98	0.61	0.21	0.25	3.44	3.88	3.44
	10.23	10.75	10.97	0.52	0.22	0.23	2.16	4.07	3.61
	11.2	11.78	11.98	0.58	0.2	0.22	3.19	3.81	3.51
	12.2	12.78	13.01	0.58	0.23	0.18	2.71	4.08	3.71
	13.19	13.77	13.97	0.58	0.2	0.26	3.77	4	3.65
	14.23	14.73	14.95	0.5	0.22	0.21	2.17	4.05	3.7
	15.16	15.71	15.95	0.55	0.24	0.19	2.44	3.98	3.95
	16.14	16.68	16.9	0.54	0.22	0.19	2.44	3.72	3.5
	17.09	17.65	17.86	0.56	0.21	0.19	2.13	4.24	4
	18.05	18.59	18.8	0.54	0.21	0.22	2.9	4.02	3.24
	19.02	19.57	19.78	0.55	0.21	0.26	2.53	4.28	4.22
	20.04	20.54	20.8	0.5	0.26	0.17	2	4.01	3.46
	20.97	21.54	21.79	0.57	0.25	0.18	2.33	4.28	3.73
	21.97	22.52	22.75	0.55	0.23	0.18	2.37	4.13	3.44
	22.93	23.49	23.73	0.56	0.24	0.19	2.37	4.26	3.72
	23.92	24.48	24.71	0.56	0.23	0.18	2.17	4.2	3.48
	24.89	25.48	25.7	0.59	0.22	0.17	2.29	4.15	3.78
	25.87	26.44	26.68	0.57	0.24	0.25	3.05	4.22	3.48
	26.93	27.44	27.65	0.51	0.21	0.21	1.95	4.12	4.04
	27.86	28.42	28.68	0.56	0.26	0.22	2.09	4.26	3.51
	28.9	29.42	29.67	0.52	0.25	0.2	2.1	4.2	3.78

AVERAGE Δt 0.5596552 0.22931034 0.2
STANDARD DEVIATION Δt 0.028596 0.0185031 0.02878492

FAST	1.13	1.68	1.9	0.55	0.22	0.14	2.87	4.51	4.35
	2.04	2.53	2.76	0.49	0.23	0.15	2.42	4.36	4.13
	2.91	3.38	3.6	0.47	0.22	0.12	3.27	4.04	4.07
	3.72	4.21	4.43	0.49	0.22	0.14	2.9	4.43	4.2
	4.57	5.06	5.28	0.49	0.22	0.16	1.97	4.48	4.41
	5.44	5.93	6.15	0.49	0.22	0.13	2.86	4.12	4.04
	6.28	6.76	6.98	0.48	0.22	0.17	2.88	4.2	4.38
	7.15	7.61	7.84	0.46	0.23	0.16	2.87	4.65	4.28
	8	8.46	8.68	0.46	0.22	0.18	1.94	4.48	4.22
	8.86	9.33	9.54	0.47	0.21	0.22	2.18	3.94	4.33
	9.76	10.18	10.39	0.42	0.21	0.15	1.93	4.5	4.08
	10.54	11.04	11.26	0.5	0.22	0.15	2.44	4.12	4.23
	11.41	11.89	12.12	0.48	0.23	0.15	3.11	4.36	4.19
	12.27	12.76	12.98	0.49	0.22	0.14	3.22	3.95	4.44
	13.12	13.6	13.82	0.48	0.22	0.15	2.68	3.92	3.41
	13.97	14.46	14.7	0.49	0.24	0.16	2.72	4.14	4.2
	14.86	15.35	15.57	0.49	0.22	0.15	2.91	4	3.89
	15.72	16.23	16.45	0.51	0.22	0.18	3	4.02	3.48
	16.63	17.09	17.33	0.46	0.24	0.16	1.97	4.23	4.33
	17.49	17.98	18.2	0.49	0.22	0.19	2.24	3.77	4.21
	18.39	18.84	19.08	0.45	0.24	0.18	2.23	4	3.94
	19.26	19.71	19.94	0.45	0.23	0.15	2.11	3.69	4.2
	20.09	21.44	21.67	1.35	0.23	0.17	2.47	4.06	4.16
	21.84	22.3	22.53	0.46	0.23	0.29	2.06	3.76	4.02
	22.82	23.2	23.36	0.38	0.16	0.19	1.96	4.18	2.9

AVERAGE Δt 0.51 0.2216 0.1652
STANDARD DEVIATION Δt 0.1777873 0.01518771 0.03380335

NORMAL	2.81	3.6	3.89	0.79	0.29	0.22	2.6	3.95	2						
	4.11	4.87	5.14	0.76	0.27	0.28	2.55	4.09	1.71						
	6.73	7.53	7.79	0.8	0.26	0.26	2.25	3.99	2.24						
	8.05	8.79	9.05	0.74	0.26	0.21	2.04	4.22	2.21						
	9.26	10.02	10.3	0.76	0.28	0.3	1.05	3.94	2.25						
	10.6	11.2	11.52	0.6	0.32	0.34	1.64	3.85	2.12						
	11.86	12.44	12.73	0.58	0.29	0.35	1.58	3.93	2.6						
	13.08	13.65	13.93	0.57	0.28	0.25	1.63	3.92	2.82						
	14.18	14.87	15.15	0.69	0.28	0.2	2.15	3.94	2.63						
	15.35	16.08	16.33	0.73	0.25	0.33	2.25	4.17	2.59						
	16.66	17.23	17.55	0.57	0.32	0.14	1.77	4.21	2.66						
	17.69	18.42	18.68	0.73	0.26	0.21	1.27	3.98	2.22						
	18.89	19.59	19.87	0.7	0.28	0.2	2.13	3.84	2.98						
	20.07	20.76	21.05	0.69	0.29	0.21	2.87	3.31	3						
	21.26	21.9	22.18	0.64	0.28	0.19	3.38	3.61	3.15						
	22.37	23.04	23.34	0.67	0.3	0.2	3.01	3.61	3.89						
	23.54	24.22	24.5	0.68	0.28	0.2	1.72	3.61	3.9						
	24.7	25.38	25.67	0.68	0.29	0.28	2.8	3.38	3.27						
	27.1	27.73	28.03	0.63	0.3	0.15	3.68	3.1	3.2						
	28.18	28.98	29.18	0.8	0.2	0.27	3.68	3.05	1.87						
29.45						3									
	AVERAGE Δt			0.6905	0.279	0.2395									
	STANDARD DEVIATION Δt			0.0745142	0.02613729	0.06004165									
FAST	6.76	7.38	7.59	0.62	0.21	0.23	3.13	4.31	3.32						
	7.82	8.33	8.52	0.51	0.19	0.22	3.69	4.5	4.22						
	8.74	9.26	9.47	0.52	0.21	0.2	2.85	4.51	4.19						
	9.67	10.18	10.42	0.51	0.24	0.18	2.61	4.17	4.4						
	10.6	11.11	11.33	0.51	0.22	0.2	3.17	4.42	4.32						
	11.53	12.04	12.27	0.51	0.23	0.18	2.4	4.43	4.54						
	12.45	12.97	13.2	0.52	0.23	0.24	3	4.36	4.07						
	13.44	13.93	14.15	0.49	0.22	0.22	2.35	4.39	4.25						
	14.37	14.87	15.11	0.5	0.24	0.18	2.92	4.03	4.11						
	15.29	15.8	16.05	0.51	0.25	0.15	2.71	4.45	4.48						
	16.2	16.75	17.01	0.55	0.26	0.16	3.48	4.41	4.49						
	17.17														
		AVERAGE Δt			0.5227273	0.22727273	0.19636364								
		STANDARD DEVIATION Δt			0.0355221	0.0200454	0.0290767								
	4	28 M	168	71.35	25.3	Overweight	SLOW	8.3	8.65	8.87	0.35	0.22	0.22	1.2	1.91
							9.09	10.08	10.28	0.99	0.2	0.33	1.7	2.45	1.74
							10.61	11.49	11.73	0.88	0.24	0.28	1.9	2.81	1.53
							12.01	12.93	14.67	0.92	1.74	0.22	2.18	3.17	2.27
							14.89	15.86	16.14	0.97	0.28	0.24	2.35	3.04	2.09
							16.38	17.27	17.48	0.89	0.21	0.42	2.21	3.22	1.73
							17.9	18.73	18.98	0.83	0.25	0.28	2.99	3.38	1.94
							19.26	20.07	20.34	0.81	0.27	0.2	2.58	3.63	2.24
							20.54	21.35	21.6	0.81	0.25	0.27	3.02	3.03	1.69
							21.87	22.7	22.95	0.83	0.25	0.31	2.22	2.74	1.82
							23.26	24.09	24.34	0.83	0.25	0.31	2.06	3.05	1.77
							24.65	25.46	25.71	0.81	0.25	0.24	2.22	3.03	1.71
							25.95						2.32		
							AVERAGE Δt			0.8266667	0.3675	0.2766667			
							STANDARD DEVIATION Δt			0.1626113	0.43283684	0.06080271			
NORMAL	2.44	3.08	3.35	0.64	0.27	0.22	2.55	3.92	2.6						
	3.57	4.19	4.49	0.62	0.3	0.15	2.12	4.1	1.7						
	4.64	5.28	5.56	0.64	0.28	0.19	2.26	3.43	2.46						
	5.75	6.33	6.59	0.58	0.26	0.19	2.53	3.55	2.26						
	6.78	7.39	7.65	0.61	0.26	0.18	3.37	3.51	1.99						
	7.83	8.46	8.73	0.63	0.27	0.17	1.72	3.94	2.83						
	8.9	9.49	9.75	0.59	0.26	0.16	3.31	3.5	2.54						
	9.91	10.5	10.79	0.59	0.29	0.16	2.21	4.1	2.62						
	10.95	11.56	11.8	0.61	0.24	0.21	2.6	3.27	2.14						
	12.01	12.69	12.93	0.68	0.24	0.25	2.68	3.47	2.71						
	13.18						2.71								
		AVERAGE Δt			0.619	0.267	0.188								
		STANDARD DEVIATION Δt			0.0299815	0.01946507	0.03119829								
	FAST	13.6	14.23	14.44	0.63	0.21	0.23	3.13	4.3	3.84					
		14.67	15.17	15.37	0.5	0.2	0.23	3.68	4.5	4.21					
15.6		16.11	16.33	0.51	0.22	0.17	2.84	4.5	4.18						
16.5		17.02	17.27	0.52	0.25	0.2	2.6	4.5	4.4						
17.47		17.95	18.18	0.48	0.23	0.2	3.16	4.41	4.32						
18.38		18.89	19.12	0.51	0.23	0.18	2.4	4.48	4.43						
19.3		19.82	20.05	0.52	0.23	0.24	3.06	4.35	4.07						
20.29		20.78	21	0.49	0.22	0.21	2.35	4.39	4.25						
21.21		21.71	21.95	0.5	0.24	0.19	2.91	4.4	4.47						
22.14		22.65	22.9	0.51	0.25	0.17	2.7	4.9	4.8						
23.07		23.6	23.9	0.53	0.3	0.13	3.47	4.31	4.48						
24.03							3.68								
		AVERAGE Δt			0.5181818	0.23454545	0.19545455								
		STANDARD DEVIATION Δt			0.0397034	0.0265946	0.03236159								

5	24 M	155	57.9	24.1 Normal	SLOW	2.44	3.08	3.36	0.64	0.28	0.21	2.55	3.93	2.6				
						3.57	4.19	4.49	0.62	0.3	0.15	2.13	4.11	1.76				
						4.64	5.28	5.56	0.64	0.28	0.19	2.26	3.44	2.46				
						5.75	6.33	6.59	0.58	0.26	0.19	2.52	2.56	2.27				
						6.78	7.4	7.65	0.62	0.25	0.18	3.38	3.51	1.99				
						7.83	8.46	8.72	0.63	0.26	0.18	1.72	3.93	2.83				
						8.9	9.49	9.75	0.59	0.26	0.24	3.32	3.5	2.55				
						9.99	10.52	10.79	0.53	0.27	0.16	2.23	4.11	2.62				
						10.95	11.56	11.8	0.61	0.24	0.21	2.6	3.27	2.14				
						12.01	12.69	12.93	0.68	0.24	0.25	2.69	2.45	2.6				
						13.18						2.72						
												AVERAGE Δt	0.614	0.264	0.196			
												STANDARD DEVIATION Δt	0.0406065	0.01897367	0.03204164			
						NORMAL	3.48	4.34	4.59	0.86	0.25	0.35	2.22	2.64	2.1			
							4.94	5.79	6.07	0.85	0.28	0.35	2.14	2.67	2.21			
							6.42	7.12	7.39	0.7	0.27	0.31	2.06	3.07	2.22			
							7.7	8.39	8.65	0.69	0.26	0.33	2.53	2.7	2.24			
							8.98	9.64	9.93	0.66	0.29	0.25	2.23	3.03	2.39			
							10.18	10.97	11.24	0.79	0.27	0.27	2.34	2.93	2.3			
11.51	12.22	12.5	0.71	0.28	0.32		2.95	3.05	2.75									
12.82	13.49	13.77	0.67	0.28	0.24		2.01	2.5	2.28									
14.01	14.78	15.07	0.77	0.29	0.24		2.72	2.95	2.21									
15.31	16.1	16.4	0.79	0.3	0.25		2.57	2.77	2.41									
16.65	17.41	17.7	0.76	0.29	0.24		2.53	2.39	2.43									
17.94	18.84	19.14	0.9	0.3	0.28		2.31	2.52	2.03									
19.42							2.51											
							AVERAGE Δt	0.7625	0.28	0.2858333								
							STANDARD DEVIATION Δt	0.078985	0.01537412	0.0437884								
FAST	4.24	5.04	5.29	0.8	0.25		0.2	2.24	2.76	3.26								
	5.49	6.16	6.44	0.67	0.28		0.21	2.63	3.3	3.16								
	6.65	7.33	7.57	0.68	0.24		0.19	2.06	2.05	3.34								
	7.76	8.42	8.69	0.66	0.27		0.21	2	3.35	3.34								
	8.9	9.49	9.76	0.59	0.27	0.22	3.42	3.48	3.52									
	9.98	10.6	10.85	0.62	0.25	0.27	2.57	4	3.48									
	11.12	11.64	11.9	0.52	0.26	0.2	2.07	3.84	3.31									
	12.1	12.69	12.97	0.59	0.28	0.19	2.55	3.37	3.22									
	13.16	13.79	14.08	0.63	0.29	0.27	3.22	3.48	3.37									
	14.35	14.93	15.19	0.58	0.26	0.25	2.06	3.15	2.95									
	15.44	16.18	16.42	0.74	0.24	0.26	3.09	3.21	2.27									
	16.68						3.09											
							AVERAGE Δt	0.6436364	0.26272727	0.22454545								
							STANDARD DEVIATION Δt	0.0786477	0.01678744	0.03173756								
	6	28 M	178	64.6	20.4 Normal	SLOW	6.47	7.42	7.59	0.95	0.17	0.55	1.7	2.01	1.96			
							8.14	9.14	9.33	1	0.19	0.62	1.78	2.02	2			
							9.95	10.65	10.82	0.7	0.17	0.51	1.68	1.95	1.93			
							11.33	12.29	12.46	0.96	0.17	0.43	1.68	1.77	1.99			
							12.89	13.92	14.09	1.03	0.17	0.54	1.93	2.04	1.84			
14.63							15.64	15.89	1.01	0.25	0.33	2.05	1.98	1.89				
16.22							17.35	17.56	1.13	0.21	0.36	2.08	1.94	1.82				
17.92							18.93	19.14	1.01	0.21	0.39	1.75	2.44	2.05				
19.53							20.52	20.73	0.99	0.21	0.54	1.88	2.04	1.85				
21.27							22.35	22.6	1.08	0.25	0.44	1.74	2.05	1.75				
23.04							24.16	24.35	1.12	0.19	0.44	2.19	2.17	1.82				
24.79							25.93	26.18	1.14	0.25	0.5	1.92	2.54	1.89				
26.68							27.9	28.16	1.22	0.26	0.4	1.74	2.22	1.84				
28.56							29.63	29.94	1.07	0.31	0.79	2.25	1.78	1.88				
30.73							32.01	32.49	1.28	0.48	0.21	1.86	2.03	2.07				
32.7							33.8	34.04	1.1	0.24	0.26	2.08	2.03	1.84				
34.3							35.46	35.7	1.16	0.24	0.45	1.77	2.06	1.93				
36.15												2.38						
							AVERAGE Δt	1.0558824	0.23352941	0.45647059								
						STANDARD DEVIATION Δt	0.1291346	0.07491171	0.13669954									
NORMAL	4.33	5.05	5.46	0.72	0.41	0.12	1.94	2.59	2.04									
	5.58	6.34	6.59	0.76	0.25	0.28	2.15	2.42	1.89									
	6.87	7.63	7.93	0.76	0.3	0.22	2.55	2.68	2.44									
	8.15	8.9	9.24	0.75	0.34	0.26	2.96	2.5	2									
	9.5	10.16	10.44	0.66	0.28	0.3	1.75	2.83	2.13									
	10.74	11.44	11.71	0.7	0.27	0.27	2.31	2.67	2.12									
	11.98	12.73	13.07	0.75	0.34	0.21	1.98	2.63	2.85									
	13.28	14.04	14.39	0.76	0.35	0.24	3.11	2.17	1.93									
	14.63	15.31	15.65	0.68	0.34	0.17	1.87	3.14	2.53									
	15.82	16.59	16.86	0.77	0.27	0.29	2.37	2.49	1.93									
	17.15	17.84	18.14	0.69	0.3	0.24	2.37	2.6	2.37									
	18.38	19.15	19.54	0.77	0.39	0.15	1.92	2.92	2.32									
	19.69	20.49	20.78	0.8	0.29	0.24	2.7	2.49	2.09									
	21.02	21.79	22.1	0.77	0.31	0.2	2.14	2.78	1.84									
	22.3						3											
							AVERAGE Δt	0.7385714	0.31714286	0.22785714								
							STANDARD DEVIATION Δt	0.0412976	0.04664573	0.05351902								

					FAST	6.01				6.57	6.83	0.56	0.26	0.15	1.9	3.57	3.03
						6.98				7.52	7.8	0.54	0.28	0.21	2.65	2.8	2.9
						8.01				8.52	8.82	0.51	0.3	0.15	1.25	3.07	3.2
						8.97				9.53	9.83	0.56	0.3	0.18	2	3.2	3.21
						10.01				10.53	10.85	0.52	0.32	0.15	2.18	2.27	2.8
						11				11.49	11.79	0.49	0.3	0.3	2.12	2.87	3.13
						12.09				12.5	12.79	0.41	0.29	0.14	1.57	2.98	2.88
						12.93				13.47	13.78	0.54	0.31	0.15	3.11	3.49	3.12
						13.93				14.45	14.74	0.52	0.29	0.15	2.56	3.4	3.04
						14.89				15.42	15.7	0.53	0.28	0.17	2.82	3.19	3
						15.87				16.4	16.73	0.53	0.33	0.16	3.36	2.34	3.26
						16.89				17.41	17.71	0.52	0.3	0.16	2	2.89	2.8
						17.87				18.45	18.75	0.58	0.3	0.12	2.97	3.23	2.36
						18.87				19.42	19.73	0.55	0.31	0.14	3.07	2.56	2.66
						19.87				20.44	20.73	0.57	0.29	0.14	3.36	2.55	2.35
						20.87				21.42	21.73	0.55	0.31	0.17	3.17	2.66	3.42
						21.9				22.42	22.7	0.52	0.28	0.13	2.46	2.86	2.44
						22.83				23.38	23.68	0.55	0.3	0.12	2.7	2.8	2.98
						23.8									2.78		

					NORMAL	19.6	20.3	20.6	0.7	0.3	0.19	2.41	3.73	2.77					
					20.79	21.5	21.79	0.71	0.29	0.25	1.2	3.57	3.19						
					22.04	22.74	23.03	0.7	0.29	0.17	2.33	2.74	2.65						
					23.2	23.91	24.2	0.71	0.29	0.22	0.96	3.74	2.95						
					24.42	25.11	25.39	0.69	0.28	0.21	2.44	3.72	3.07						
					25.6	26.3	26.6	0.7	0.3	0.19	1.98	3.29	3.77						
					26.79	27.48	27.78	0.69	0.3	0.19	3.66	3.68	3.73						
					27.97	28.68	28.98	0.71	0.3	0.18	3.63	3.47	3.66						
					29.16	29.89	30.19	0.73	0.3	0.19	1.46	3.28	2.58						
					30.38	31.09	31.39	0.71	0.3	0.2	1.12	3.64	2.64						
					31.59	32.28	32.63	0.69	0.35	0.22	1.41	3.62	2.2						
					32.85	33.56	33.84	0.71	0.28	0.21	2.86	2.89	2.09						
					34.05	34.74	35.04	0.69	0.3	0.23	2.56	3.49	2.73						
					35.27	35.94	36.23	0.67	0.29	0.23	2.43	4	2.8						
					36.46	37.14	37.45	0.68	0.31	0.22	3.28	3.38	3.34						
					37.67						2.17								
					AVERAGE Δt	0.6993333 0.29866667 0.20666667													
					STANDARD DEVIATION Δt	0.0148645 0.01641718 0.02193063													
					FAST	10.78	11.38	11.67	0.6	0.29	0.16	2.88	4.12	3.98					
					11.83	12.39	12.69	0.56	0.3	0.31	2.58	3.12	4.01						
					13	13.46	13.74	0.46	0.28	0.18	1.65	4.28	3.74						
					13.92	14.49	14.78	0.57	0.29	0.17	2.01	4.21	3.61						
					14.95	15.53	15.8	0.58	0.27	0.17	2	4.52	3.81						
					15.97	16.56	16.85	0.59	0.29	0.18	1.2	3.94	3.81						
					17.03	17.6	17.9	0.57	0.3	0.17	2	3.84	3.9						
					18.07	18.65	18.95	0.58	0.3	0.17	1.91	4.12	4						
					19.12	19.7	20.01	0.58	0.31	0.17	2.28	4.3	3.75						
					20.18	20.76	21.05	0.58	0.29	0.18	1.85	3.56	3.59						
					21.23	21.82	22.11	0.59	0.29	0.16	1.35	3.95	4.21						
					22.27	22.86	23.15	0.59	0.29	0.3	2.61	4.07	3.04						
					23.45	23.9	24.2	0.45	0.3	0.17	1.72	4.02	3.82						
					24.37	24.95	25.23	0.58	0.28	0.22	1.67	4.13	3.8						
					25.45	26.01	26.29	0.56	0.28	0.31	2.34	3	3.09						
					26.6						1.72								
					AVERAGE Δt	0.5626667 0.29066667 0.20133333													
					STANDARD DEVIATION Δt	0.0451136 0.01032796 0.05629852													
9	30 M	153	65	27.8	Overweight SLOW	20.46	21.11	21.35	0.65	0.24	0.25	2.52	3	2.24					
					21.6	22.27	22.56	0.67	0.29	0.21	3.24	2.75	2.16						
					22.77	23.48	23.73	0.71	0.25	0.22	2.31	2.07	3						
					23.95	24.64	24.98	0.69	0.34	0.18	2.33	2.78	2.03						
					25.16	25.84	26.12	0.68	0.28	0.19	2.44	3.09	2.22						
					26.31	27.01	27.27	0.7	0.26	0.22	3.12	2.41	2.07						
					27.49	28.16	28.53	0.67	0.37	0.15	2	2.48	2.02						
					28.68	29.37	29.69	0.69	0.32	0.16	3.12	3.25	1.99						
					29.85	30.54	30.86	0.69	0.32	0.18	2.85	2.08	2.34						
					31.04	31.73	31.97	0.69	0.24	0.22	1.93	3.45	2.02						
					32.19						2								
										AVERAGE Δt	0.684 0.291 0.198								
										STANDARD DEVIATION Δt	0.017127 0.04508018 0.03119829								
										NORMAL	9.89	10.73	10.97	0.84	0.24	0.29	2.44	2.63	2.32
										11.26	11.98	12.28	0.72	0.3	0.22	2.59	3.02	2.11	
										12.5	13.26	13.48	0.76	0.22	0.29	2.29	2.23	2.27	
										13.77	14.49	14.69	0.72	0.2	0.32	2.39	3.65	2.28	
15.01	15.65	15.9	0.64	0.25						0.3	2.14	3.29	2.25						
16.2	16.97	17.19	0.77	0.22						0.27	2.1	3.39	2.03						
17.46	18.17	18.41	0.71	0.24						0.33	3.16	3.37	1.83						
18.74	19.4	19.65	0.66	0.25						0.25	2	3.16	3.32						
19.9	20.6	20.88	0.7	0.28						0.31	1.78	2.54	2.88						
21.19	21.95	22.24	0.76	0.29						0.25	1.76	2.34	2.8						
22.49											1.7								
										AVERAGE Δt	0.728 0.249 0.283								
										STANDARD DEVIATION Δt	0.0576965 0.03247221 0.03497618								
										FAST	10.08	10.57	10.83	0.49	0.26	0.21	2.02	3.76	3.02
										11.04	11.52	11.79	0.48	0.27	0.18	2.04	3.72	2.7	
										11.97	12.48	12.74	0.51	0.26	0.16	2.66	3.67	3.02	
					12.9	13.45	13.7	0.55	0.25	0.22	2.01	3.89	2.85						
					13.92	14.42	14.67	0.5	0.25	0.15	1.93	3.84	3						
					14.82	15.37	15.63	0.55	0.26	0.19	3.67	4.07	2.72						
					15.82	16.3	16.59	0.48	0.29	0.25	2.07	3.17	1.97						
					16.84	17.39	17.64	0.55	0.25	0.19	2.23	3.76	2.27						
					17.83	18.37	18.62	0.54	0.25	0.21	2.27	3.69	3.62						
					18.83	19.38	19.63	0.55	0.25	0.2	2.42	3.43	1.88						
					19.83						2.5								
										AVERAGE Δt	0.52 0.259 0.196								
										STANDARD DEVIATION Δt	0.0309121 0.01286684 0.0291357								
					10	24 M	162.5	52	19.7	Normal SLOW	17.24	18.29	18.56	1.05	0.27	0.26	2.04	2.03	1.56
										18.82	19.98	20.3	1.16	0.32	0.2	2.21	1.63	1.65	
										20.5	21.74	22.03	1.24	0.29	0.32	2.53	2.72	1.57	
22.35	23.33	23.54	0.98	0.21						0.26	2.32	1.76	1.86						
23.8	24.7	25.24	0.9	0.54						0.23	1.54	1.74	1.67						
25.47	26.5	26.86	1.03	0.36						0.16	1.28	1.97	1.7						
27.02	27.98	28.35	0.96	0.37						0.15	1.2	1.98	1.65						
28.5	29.53	29.8	1.03	0.27						0.26	2.69	1.89	2						
30.06	31.07	31.38	1.01	0.31						0.18	1.9	1.9	1.97						
31.56	32.56	32.9	1	0.34						0.3	2.68	1.86	2						
33.2											2.66								
										AVERAGE Δt	1.036 0.328 0.232								
										STANDARD DEVIATION Δt	0.0981156 0.0884182 0.0580804								

NORMAL	9.89	10.73	10.97	0.84	0.24	0.29	2.5	3.63	2.32
	11.26	11.9	12.29	0.64	0.39	0.21	2.59	3.01	2.21
	12.5	13.26	13.48	0.76	0.22	0.29	2.8	3.22	2.27
	13.77	14.49	14.69	0.72	0.2	0.32	2.38	3.65	2.17
	15.01	15.66	15.9	0.65	0.24	0.37	2.44	3.29	2.62
	16.27	16.97	17.19	0.7	0.22	0.27	2.09	3.49	2.03
	17.46	18.18	18.41	0.72	0.23	0.3	3.15	3.37	1.82
	18.71	19.39	19.65	0.68	0.26	0.25	1.78	3.37	2.3
	19.9	20.6	20.82	0.7	0.22	0.37	1.78	2.5	1.87
	21.19	21.75	22.11	0.56	0.36	0.17		2.82	
	22.28								
		AVERAGE Δt		0.697	0.258	0.284			
		STANDARD DEVIATION Δt		0.0745431	0.06408328	0.06345602			
FAST	5.27	5.75	6.01	0.48	0.26	0.21	1.75	3.42	3.05
	6.22	6.71	6.98	0.49	0.27	0.28	2.5	3.42	3.33
	7.26	7.68	7.98	0.42	0.3	0.17	2.24	3.5	2.8
	8.15	8.64	8.92	0.49	0.28	0.17	1.65	3.47	3.37
	9.09	9.61	9.87	0.52	0.26	0.21	2.63	3.28	3.12
	10.08	10.57	10.82	0.49	0.25	0.22	1.82	3.24	3.13
	11.04	11.52	11.79	0.48	0.27	0.18	2.86	2.83	3.2
	11.97	12.48	12.74	0.51	0.26	0.16	1.77	3.69	3.48
	12.9	13.45	13.7	0.55	0.25	0.22	2.28	3.65	3.53
	13.92	14.42	14.67	0.5	0.25	0.15	2.57	3.26	3.09
	14.82	15.37	15.63	0.55	0.26	0.19	2.8	3.57	3.39
	15.82						1.9		
		AVERAGE Δt		0.4981818	0.26454545	0.19636364			
		STANDARD DEVIATION Δt		0.0360051	0.01507557	0.03695206			

Table 2: - Data Table showing time points and time intervals between peaks of Gait cycle.

In the experimental data table 5 normal and 5 overweight individual data have been provided. Getting the average data from all the time-series helps us to analyse the difference in their datasets.

5.6 Data Analysis

From the experimental data table average data of time intervals is found out. That average data in Table 3 helps us in distinguishing the datasets of normal and overweight persons.

SUB_ID	STATUS	WALK_STY LE	STANCE (sec)	SWING (sec)	Stride (sec)	SD_Stance (sec)	SD_Swing (sec)
01.	OW (BMI 26.6)	SLOW	0.66 (56.4%)	0.51 (43.6%)	1.17	0.087	0.102
		NORMAL	0.56 (56.6%)	0.43 (43.4%)	0.99	0.028	0.047
		FAST	0.51 (56.7%)	0.39 (43.3%)	0.9	0.178	0.049

02.	OW (BMI 27.9)	SLOW	1.02 (60.2%)	0.675 (39.8%)	1.695	0.089	0.110
		NORMAL	0.65 (56.5%)	0.5 (43.5%)	1.15	0.029	0.032
		FAST	0.52 (55.3%)	0.42 (44.7%)	0.94	0.044	0.058
03.	NW (BMI 22.3)	SLOW	1.01 (64%)	0.571 (46%)	1.585	0.062	0.116
		NORMAL	0.69 (57.1%)	0.52 (42.9%)	1.21	0.07	0.086
		FAST	0.52 (55.2%)	0.423 (44.8%)	0.945	0.035	0.049
04.	OW (BMI 25.3)	SLOW	0.827 (56.2%)	0.644 (43.8%)	1.471	0.163	0.493
		NORMAL	0.619 (57.6%)	0.455 (42.4%)	1.074	0.029	0.049
		FAST	0.518 (54.7%)	0.429 (45.3%)	0.947	0.039	0.058
05.	NW (BMI 24.1)	SLOW	0.614 (57.2%)	0.46 (42.8%)	1.07	0.041	0.051
		NORMAL	0.763 (57.4%)	0.566 (42.6%)	1.329	0.078	0.059
		FAST	0.644 (56.9%)	0.487 (43.1%)	1.131	0.78	0.049
06.	NW (BMI 20.4)	SLOW	1.056 (60.5%)	0.69 (39.5%)	1.746	0.129	0.212
		NORMAL	0.739 (57.6%)	0.545 (42.4%)	1.283	0.041	0.1
		FAST	0.531	0.458	0.989	0.037	0.057

			(53.7%)	(46.3%)			
07.	NW (BMI 21)	SLOW	0.711 (51.5%)	0.671 (42.5%)	1.138	0.066	0.095
		NORMAL	0.695 (56%)	0.546 (44%)	1.241	0.039	0.0556
		FAST	0.541 (51.4%)	0.512 (48.6%)	1.053	0.061	0.074
08.	OW (BMI 28)	SLOW	0.705 (57.7%)	0.517 (42.3%)	1.22	0.042	0.057
		NORMAL	0.699 (58%)	0.506 (42%)	1.205	0.148	0.038
		FAST	0.563 (53.4%)	0.492 (46.6%)	1.055	0.045	0.066
09.	OW (BMI 27.8)	SLOW	0.684 (58.3%)	0.489 (41.7%)	1.173	0.017	0.076
		NORMAL	0.728 (57.8%)	0.532 (42.3%)	1.26	0.057	0.067
		FAST	0.52 (53.3%)	0.455 (46.7%)	0.975	0.031	0.041
10.	NW (BMI 19.7)	SLOW	1.036 (65%)	0.56 (35.1%)	1.59	0.098	0.146
		NORMAL	0.697 (56.2%)	0.542 (43.8%)	1.239	0.07	0.127
		FAST	0.498 (51.9%)	0.46 (48.1%)	0.958	0.036	0.051

Table 3 :- Average Stance Time, Swing Time, Stride Time for Normal and Overweight persons during different walking patterns (NW – Normal Weight, OW - Overweight)

5.7 Discussion

The range of average stance time, swing time and stride time are studied for volunteers of different BMI ranges for different walking patterns. The findings are listed below in Table 03

Serial Number	Points of Difference	Walking Style	Normal weighted	Overweighted
			(secs)	(secs)
01.	STANCE TIME	SLOW	0.614- 1.056 (51.4% - 64.9%)	0.66-1.02 (56.2% - 60.2%)
		NORMAL	0.691 – 0.763 (56%- 57.6%)	0.56 – 0.73 (56.5%- 58.2%)
		FAST	0.498 – 0.644 (51.4%- 56.9%)	0.51 – 0.56 (53.3% - 56.7%)
02.	SWING TIME	SLOW	0.46 – 0.69 (35.1% - 48.5%)	0.489 – 0.675 (39.8%-43.8%)
		NORMAL	0.519 – 0.546 (42.5% - 44%)	0.43-0.53 (42%-43.5%)
		FAST	0.423 – 0.512 (43.1% - 48.6%)	0.39-0.49 (43.3% - 46.6%)
03	STRIDE TIME	SLOW	1.074 – 1.076	1.17-1.695
		NORMAL	1.21 – 1.33	0.99 – 1.26
		FAST	0.945 – 1.13	0.9-1.055

Table 4: - Range of average Stance Time, Swing Time, Stride Time of normal and overweight individuals for different walking patterns

5.8 Inference

- For normal walking, the time difference between maximum and minimum **stance time** (0.07 for normal and 0.17 for overweight), **swing time** (0.03 for normal and 0.1 for overweight) and **stride time** (0.12 for normal and 0.27 for overweight) of overweight persons is **greater** than normal persons.
- For slow walking, the time difference between maximum and minimum **stance time** (0.5 for normal and 0.36 for overweight), **swing time** (0.23 for normal and 0.19 for overweight) and **stride time** (0.002 for normal and 0.53 for overweight) of overweight persons is **lesser** than normal persons.
- For fast walking, the time difference between maximum and minimum **stance time** (0.14 for normal and 0.05 for overweight), **swing time** (0.09 for normal and 0.1 for overweight) and **stride time** (0.19 for normal and 0.16 for overweight) of overweight persons is **lesser** than normal persons.
- Since the variance of Gait parameters of normal persons is higher than overweight persons the normal weighted persons are more diverse and overweighted persons are less versatile.
- The swing time will be lesser for overweight individuals owing to their greater weight while swing time is comparatively higher in normal volunteers.

Chapter 6

Conclusion

A wearable single sensor (accelerometer) has been used to measure the acceleration of person's foot. The output obtained being noisy is made noiseless by passing the output signal through a Kalman Filter. Peak detection algorithm is performed over the estimated signal to point out the time points of occurrence of Gait parameters. Further, the study is extended to 25 individuals of different BMI. The effect of BMI on the foot accelerometer data has been studied thereafter. It has been inferred that overweight person have lesser swing time than normal persons.

Chapter 7

Future Scope

In this research, a study has been made between the normal and the overweight persons. Spatiotemporal Gait parameters or time intervals calculated between the Gait parameters provides an insight regarding the BMI of the person. This work can be extended further by applying Artificial Intelligence (AI) and Machine Learning (ML) on the datasets to come up with a more prominent inference. This prototype can be used to record patients' data who are suffering from Parkinson's Disease, Arthritis or have any disability. Comparative study can be done between the healthy individuals and the patients to compare stance time, swing time and stride time. Two accelerometer sensor or a gyroscope makes it suitable to record joint angles also. In that case, instead of Kalman Filtering we have to use Extended Kalman filtering. Making the prototype wireless will also make the experimentation much easier.

APPENDIX A

Arduino IDE Code

The accelerometer Adxl345 code written in Arduino IDE programming language is given below. Nano Arduino is used as the microcontroller here. The sensor frequency is kept as 100 Hz and the baud rate is 230400 bits. Sampling frequency comes out to be 130 samples/sec.

```
//Add the SPI library so we can communicate with the ADXL345 sensor
#include <SPI.h>

/*#define ADXL345_MG2G_MULTIPLIER (0.004) ///< 4mg per lsb
#define SENSORS_GRAVITY_EARTH (9.80665F) ///< Earth's gravity in m/s^2
#define SENSORS_GRAVITY_MOON (1.6F)    ///< The moon's gravity in m/s^2
#define SENSORS_GRAVITY_SUN (275.0F)    ///< The sun's gravity in m/s^2
#define SENSORS_GRAVITY_STANDARD (SENSORS_GRAVITY_EARTH)
*/

double ADXL345_MG2G_MULTIPLIER =0.004; ///< 4mg per lsb
double SENSORS_GRAVITY_EARTH =9.80665F; /**< Earth's gravity in m/s^2 */
double SENSORS_GRAVITY_MOON =1.6F;    /**< The moon's gravity in m/s^2 */
double SENSORS_GRAVITY_SUN =275.0F;    /**< The sun's gravity in m/s^2 */
double SENSORS_GRAVITY_STANDARD =SENSORS_GRAVITY_EARTH;

//Assign the Chip Select signal to pin .
int CS=10;

//This is a list of some of the registers available on the ADXL345.
//To learn more about these and the rest of the registers on the ADXL345, read the datasheet!
char POWER_CTL = 0x2D; //Power Control Register
char BW_RATE = 0x2c;
char DATA_FORMAT = 0x31;
char DATA0 = 0xB2; //X-Axis Data 0
char DATA1 = 0xB3; //X-Axis Data 1
```

```

char DATAY0 = 0xB4; //Y-Axis Data 0
char DATAY1 = 0xB5; //Y-Axis Data 1
char DATAZ0 = 0xB6; //Z-Axis Data 0
char DATAZ1 = 0xB7; //Z-Axis Data 1

//This buffer will hold values read from the ADXL345 registers.
uint8_t values[6];
//These variables will be used to hold the x,y and z axis accelerometer values.
int16_t x,y,z;
byte buff;

void setup(){
  //Initiate an SPI communication instance.
  SPI.begin();
  SPI.setClockDivider(4); // 8 to get 2MHz
  //Configure the SPI connection for the ADXL345.
  SPI.setDataMode(SPI_MODE3);
  //Create a serial connection to display the data on the terminal.
  Serial.begin(230400);
  //Serial.begin(1000000);

  //Set up the Chip Select pin to be an output from the Arduino.
  pinMode(CS, OUTPUT);
  //Before communication starts, the Chip Select pin needs to be set high.
  digitalWrite(CS, HIGH);
  delayMicroseconds(1);

  char rate_code=0b1111;

  digitalWrite(CS, LOW); SPI.transfer(POWER_CTL); SPI.transfer(0x08); digitalWrite(CS,
HIGH); delayMicroseconds(1);

```

```

    digitalWrite(CS, LOW); SPI.transfer(BW_RATE); SPI.transfer(0b00001010 & rate_code);
    digitalWrite(CS, HIGH); delayMicroseconds(1);

    // left justified

    digitalWrite(CS, LOW); SPI.transfer(DATA_FORMAT); SPI.transfer(0b00000100);
    digitalWrite(CS, HIGH); delayMicroseconds(1);

    // right justified

    //digitalWrite(CS, LOW); SPI.transfer(DATA_FORMAT); SPI.transfer(0b00000100);
    digitalWrite(CS, HIGH); delayMicroseconds(1);
}

```

```

void loop(){
    digitalWrite(CS, LOW); SPI.transfer(DATA_X0); values[0] = SPI.transfer(0x00);
    digitalWrite(CS, HIGH); delayMicroseconds(1);

    digitalWrite(CS, LOW); SPI.transfer(DATA_X1); values[1] = SPI.transfer(0x00);
    digitalWrite(CS, HIGH); delayMicroseconds(1);

    digitalWrite(CS, LOW); SPI.transfer(DATA_Y0); values[2] = SPI.transfer(0x00);
    digitalWrite(CS, HIGH); delayMicroseconds(1);

    digitalWrite(CS, LOW); SPI.transfer(DATA_Y1); values[3] = SPI.transfer(0x00);
    digitalWrite(CS, HIGH); delayMicroseconds(1);

    digitalWrite(CS, LOW); SPI.transfer(DATA_Z0); values[4] = SPI.transfer(0x00);
    digitalWrite(CS, HIGH); delayMicroseconds(1);

    digitalWrite(CS, LOW); SPI.transfer(DATA_Z1); values[5] = SPI.transfer(0x00);
    digitalWrite(CS, HIGH); delayMicroseconds(1);
}

```

//The ADXL345 gives 10-bit acceleration values, but they are stored as bytes (8-bits). To get the full value, two bytes must be combined for each axis.

//The X value is stored in values[0] and values[1].

//The Y value is stored in values[2] and values[3].

x= int16_t(values[1]) <<8 | int16_t(values[0]);

y= int16_t(values[3]) <<8 | int16_t(values[2]);

z= int16_t(values[5]) <<8 | int16_t(values[4]);

x= x>>6; y= y>>6; z= z>>6; // left justified

```
//x= x & 0x01ff; y= y & 0x01ff; z= z & 0x01ff;// right justified
```

```
//Print the results to the terminal.
```

```
float x_cal = x/1200.00;
```

```
float y_cal = y/3500.00;
```

```
float z_cal = z/110.00;
```

```
Serial.print(x_cal, DEC); Serial.print(',');
```

```
Serial.print(y_cal, DEC); Serial.print(',');
```

```
Serial.println(z_cal, DEC);
```

```
delayMicroseconds(10000); //delay(10);
```

```
}
```

APPENDIX B

MATLAB code

The measured output from the Arduino is sent through a Kalman filter to make the output noiseless. The program required for this purpose is mentioned below.

```
dt = 0.001;
measnoise_z = 0.00429;
accelnoise = 0.002;
F = [1 -1 dt -dt 0.5*dt^2 -0.5*dt^2; 0 1 0 0 0 0; 0 0 1 0 dt -dt; 0 0 0 1 0 0; 0 0 0 0 1 0; 0 0 0 0
0 1]; % State Transition Matrix
H = [0 0 0 0 1 0];
x_hat = [0;0;0;0;0;0];
R_z = (measnoise_z^2);
Q = [dt^4/4 -dt^4/4 dt^3/2 -dt^3/2 dt^2/2 -dt^2/2 ; dt^4/4 -dt^4/4 dt^3/2 -dt^3/2 dt^2/2 -
dt^2/2; dt^3/2 -dt^3/2 dt^2 -dt^2 dt -dt ; dt^3/2 -dt^3/2 dt^2 -dt^2 dt -dt; dt^2/2 -dt^2/2 dt -dt
1 -1; dt^2/2 -dt^2/2 dt -dt 1 -1]* (accelnoise^2); % Process Noise matrix
P = 500; % Initialising the covariance
I = eye(6);
Val = 0; Index = 0;
numz = xlsread('cal_shoe_foot5.xlsx', 'E1:E2626');
lz = length(numz);
fs = 130;
tz = (1:lz)/fs;

acchatz = [];
accmeasz = [];
gain = [];

for o = 1:lz
    z = numz(o);
    x_hat = F*x_hat ; % State Extrapolation Equation
    P = F*P*F' + Q ; % Covariance Extrapolation Equation
    K = P*H'/(H*P*H' + R_z); % Kalman gain matrix
    x_hat = x_hat + K*((z) - H*x_hat); % State Update Equation
    P = (I - K*H)*P*(I - K*H)' + K*R_z*K'; % Covariance Update Equation
    if (x_hat(5) >= Val)
        Val = x_hat(5);
        Index = (o/fs);
    end

accmeasz = [accmeasz; z];
acchatz = [acchatz; x_hat(5)];
```

```

    gain = [gain; K(5)];
end
close all;
figure;

plot(tz, accmeasz, 'r-', 'Linewidth', 2);
grid on;
xlabel('Time(sec)');
ylabel('Measured Acceleration (m/sec^2)');
legend('Z axis');

figure;
tz=tz(1550:1850);
acchatz = acchatz(1550:1850);
plot( tz, acchatz, 'r-', 'Linewidth', 2);

findpeaks(acchatz,tz, 'MinPeakHeight', 1, 'MinPeakDistance', 0.08);

xt = [ 12.13 12.36 12.45 12.66 12.85 13.08 13.16 13.26 13.35 13.5 13.6 13.82 13.95 14.06];
yt = [ 3.71 4.11 2.66 1.11 3.82 4.14 3.02 1.22 1.25 1.23 3.75 3.99 2.73 1.14];
str = {'TO','MSW', 'HS', 'MST', 'TO', 'MS', 'HS', 'FF', 'MST','HO', 'TO', 'MSW', 'HS', 'FF'};
text(xt, yt, str);

grid on;
xlabel('Time(sec)');
ylabel('Estimated Acceleration (m/sec^2)');
legend('Z axis');

tz = linspace(0, 1, length(gain));
figure;
plot( tz, gain, 'b-', 'Linewidth', 2);
grid on;
xlabel('Time(sec)');
ylabel('Kalman Gain');
legend('Kalman Gain');

```

APPENDIX C

Publications Made:

- **JOURNALS**

1. Basu, P., Ramdhun, Y., and Avvari, R.K, May, 2022. A deep learning framework for screening locomotive disorders using single inertial sensor placed on mid-metatarsal side – a primer for futuristic wearables in smart socks technology

Status: Under final preparation

- **BOOK CHAPTERS**

1. Basu, P., and Avvari, R.K, May, 2022. Prospects of wearable inertial sensors for assessing performance of sports person using machine learning algorithms in "*Image Processing and Intelligent Computing Systems*" CRC Press, Taylor & Francis Group.

Status: Accepted.

2. Ramdhun, Y., Basu, P., Avvari, R.K, and Thirugnanam A., March, 2022. Biomechanics of an Avian Flight : Exploration of the complex interactions Between the Musculoskeletal, Sensory and Neural Systems in *Advances in Computational Approaches in Biomechanics*, Chapter 14, Page Number: 223-243.

Status: Published on 20th March, 2022.

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