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Wearable Coach For Symmetric Walking

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I would like to dedicate my thesis to my beloved grandfathers -
Sai Babu Rali & Sriramulu Seelam

Abstract

The cartilage in hip and knee joints degenerates due to aging and continuous use (ex: walking). The walking style is altered due to this hip/knee problem, resulting in an asymmetric gait. This process has the potential to have long-term impacts on walking gait, injure healthy lower limbs, and require users to have knee/hip replacement surgery (prosthesis). Patients who have a prosthesis go through physiotherapy sessions to re-learn symmetric gait. These sessions intend to re-train the patient's kinaesthetic feedback, altered due to the asymmetric gait. Unfortunately, when patients like to practice outside therapy sessions, the feedback generally provided by the physiotherapist is unavailable. In recent years, the use of wearable devices in analyzing gait has been increasing gradually because of their size, flexibility, and functioning capabilities.

This thesis aims to identify the criteria for asymmetries present in users with hip/knee prostheses and develop a wearable device to assist the user in overcoming asymmetric walking in real-time. We conducted an interview with a physiotherapist to understand the asymmetries in walking for the patients with prostheses. From the literature reading, we concluded a criterion (hypothesis based on intermediate step duration) for identifying asymmetric walking using heel-strike events.

In the earlier phases, we performed experiments on users with and without prostheses to understand and determine symmetric and asymmetric walking criteria. In parallel, we designed a wearable device and developed a real-time algorithm based on the hypothesis criterion. Later in the following stages, we performed a definitive study to verify the hypothesis and the possibility to derive more criteria for addressing asymmetries in walking. However, this study's results are not supporting the hypothesis criterion in identifying asymmetries. Also, the users with hip/knee prostheses showed diverse walking patterns, which demonstrated possibilities of asymmetries present during other walking events. This observation led to the implementation of real-time machine learning as an experiment to verify the feasibility of distinguishing symmetric and asymmetric walking.

By the end of this thesis, we identified few asymmetries in walking performed by users with prostheses. Also, the standard way of employing single/multiple criteria to recognize asymmetry in walking presented by users with hip/knee prostheses requires more work to discover the appropriate criteria. Providing feedback to users is a future work to perform. However, the designed waist belt and lower back location on the human body have the ability to detect asymmetry and deliver feedback to the user for motor re-learning.

Acknowledgements

This thesis concludes my Master's program in Embedded Systems at the University of Twente. This experience that started in 2019 has been more challenging and lively than I could have expected/planned at the beginning, which makes the completion of my Masters degree very purposeful.

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Sai Kishan Rali
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Chapter 1

Introduction

Walking is regarded as the most underrated exercise because it does not demand any post or pre-workout routine or machinery and is free of cost. This leaves an impression of not being a very effective exercise to perform. However, it is one of the essential activities of an individual in their entire life. It contributes to many health benefits, mental boost, and the number of days one can think of in a hospital each year. Many studies are supporting this argument[1], and experts are spreading the importance and provide tips to make the most out of the walking[2]. This additionally includes "psychologists finding that a 10-minute walk may be just as good as a 45-minute workout when it comes relieving the symptoms of anxiety."

A healthy activity like walking coupled with aging can cause difficulties for the joints movement, especially for the lower limbs. This primarily affects the cartilage present in the joints, which becomes rugged, irregular, and worn out because of the activities. This degenerative condition is labeled as Arthrosis[3]. The person suffering from arthrosis can have pain and loss of mobility of the joint. This results in less activity of any one side or both sides of the lower limbs. Especially for walking, during this reduction phase, the user develops/modifies the way of walking unknowingly, i.e., trying to reduce the load on the unhealthy lower limb. Moreover, the ideal way of walking (symmetric walking) is gradually changed into an abnormal form of walking (asymmetric walking) and alters the learned kinaesthetic feedback on certain joints and training the brain to learn the new but unhealthy body movements for walking. These abnormalities and the rate of damage in the lower limbs differ among individuals. This abnormal walking results in degradation of the joints in the healthy side, which increases the chances of damaging the joints of the healthy side. This ultimately results in a long-term effect on the healthy side and a complete loss of mobility due to pain or insufficient strength to actuate the lower limbs.

[1]https://www.health.harvard.edu/staying-healthy/walking-your-steps-to-health
[2]https://www.nbcnews.com/better/health/why-walking-most-underrated-form-exercise-ncna797271
[3]https://www.medicinenet.com/arthrosis/definition.htm

In most cases, treatment only begins when the arthrosis is already noticeably painful and causes significant joint changes. The treatment of arthrosis pursues two objectives - pain relief and restoring mobility through surgery. Depending on the natural progression of the arthrosis, multiple treatment methods are applied like heat, water, and ice treatments, electrotherapy, and physiotherapy. Moreover, there are aids like cushioned heels, wedge cushions, seat raisers, supportive orthoses, bandages, and walking sticks or crutches to assist the patients in having symmetric walking. However, avoiding surgery is not always possible. The surgery performed on patients can result in having prostheses in joints. After the surgery, the patients will be relieved from pain, but the kinaesthetic feedback for those joints is affected. Because of the loss of the kinaesthetic feedback, the body has to re-learn the same motor skills (e.g., walking). This is achieved with the help of physiotherapists in rehabilitation centers. In the case of lower limbs, the physiotherapists administer muscle strengthening, stretching, and coordination training[4]. By undergoing this, the brain will begin recognizing the motion based on the body's position at a given time/activity. This results in patients having the correct kinaesthetic feedbacks for the joints with the prosthesis.

The processes of regaining the necessary kinaesthetic feedback for right body movements take time. It cannot be achieved in few days. The improvement of the body movements should occur under a physiotherapist's guidance to ensure the prostheses joints deliver the correct kinaesthetic feedback. More training of those joints with proper guidance leads to better learning of the kinaesthetic feedback at those joints. Therefore eliminating wrong body movements before surgery (asymmetry walking) and after surgery (motor learning of walking) are both critical. However, with an active lifestyle, the patients attend the physiotherapists in limited sessions per week. They bear their responsibility to alter their routine behavior, modify their physical exertion at work, and exercise by themselves. The motivation/feedback for the patient to develop this kinaesthetic feedback on the joints is provided effectively when they train with physiotherapists but is absent when they exercise by themselves. This lack of feedback can delay/or reduce the effectiveness of the treatment to develop the motion routine.

As advancements in technology are increasing, proper feedback can be provided without the help of a physiotherapist. This feedback helps in learning the correct body motion required for symmetric walking. This is made possible with the use of wearable technology. The term wearable technology refers to any electronic device that can be worn on a human body. The most common type of wearable for measuring gait is designed by using inertial sensors. These sensors use inertia to detect linear accelerations by using accelerometers or angular velocities by using gyroscopes. Standardly, an inertial measurement unit (IMU) accommodates necessary inertial measuring devices like a 3-axis accelerometer, 3-axis gyroscopes, in some cases, a 3-axis magnetometer. Wearable devices are portable, allowing people with a wide range of movement disorders to benefit from analysis and intervention approaches previously exclusively available in research labs and medical clinics. Demand for wearable computational devices has lowered the cost of the inertial sensor and actuation components while also driving technical progress to enable long-term (hours and days) continuous usage. As a result, wearable sensing and feedback devices demonstrate a growing potential to deliver significant therapeutic advantages to the public [64].

[4] https://www.fysiomasters.nl/en/physiotherapy/arthrosis/

Optical motion analysis systems used in laboratories are still the gold standard for gait analysis. However, they are expensive, resource-consuming, and generally immobile, limiting their use in research and clinical contexts [66]. Even though laboratory studies are usually well-controlled, they may always be incapable of replicating real-life circumstances. Practical constraints limit the time that participants can spend testing in a laboratory. In contrast, wearable devices may theoretically be worn constantly throughout the day for months or even years. This constant monitoring is at the center of the Quantified Self-movement [69], as it is more likely to provide an accurate image of human mobility reality than short-term laboratory research. Wearable devices utilized for lengthy periods might allow for gait evaluations and treatments that were previously impossible. Recent technology developments, on the other hand, have caused an increase in the adoption of more inexpensive, easy-to-use, and accessible wearable sensors for gait measurement [70].

The wearable design choice for this thesis is to ensure the minimalist usage of sensors located on a human body to meet the functionality requirements. The term minimalist addresses the number of body locations used in obtaining the gait parameters with the help of sensors, i.e., not to crowd the user's body with sensors making the wearable device less desirable to use. This approach contains the potential to increase the complexity in determining/obtaining specific gait parameters, which can be obtained easily with more sensors located on the body. However, this trade-off leads to a more convenient and portable device for the user to use. When it comes to wearable devices, the product's comfort can be just as important to the user as the device's function. A machine can perform its function perfectly, but if it is uncomfortable to wear or put on, it will not be used for very long. Plus, another criterion chosen for this wearable device is to be a standalone device. This reduces the possibility of additional distractions caused when it is integrated with other portable devices (e.g., smartphones). This can result in a better concentration environment for the user when performing the walking activity in their homes or comfortable surroundings at their will. This device also can eliminate the dependency on another human being to watch/guide the user's walking activity.

Moreover, the feedback type and location of the feedback are other targeted areas of this thesis. To assist the user in their progress of relearning the lost motor skills, the designed wearable hosts, the necessary components to monitor and provide feedback to the user relearning process. This feedback activation is also planned in real-time, meaning to provide feedback immediately during the practice of their activity. This immediate/concurrent feedback could be more effective in re-learning a movement rather than knowing the analytical statistics provided traditionally after the user finishes their training for every session. The location to provide feedback also weighs in the user experience/effectiveness of using a wearable device. For this thesis, identifying the type of feedback and location of feedback for the patients with prostheses represents a crucial task.

Overall, wearables are small, equipped with sensors and processors to observe the patient's movements and provide feedback/motivation when needed. By doing this, the user develops the correct kinaesthetic feedback in prostheses joints for symmetric walking. This thesis explores possible asymmetric walking gaits, locations for feedback, wearables, and different feedback strategies to encourage patients to overcome asymmetric walking. By performing this, it aids the patient to practice their symmetry walking routine anytime at their will rather than waiting for physiotherapy sessions to provide feedback. With this, the effectiveness of the patient's walking may be increased and the recovery time reduced.

1.1 Goal

The cartilage present in hip/knee joints undergoes degenerative processes due to aging/ frequent usage. Because of this condition in the hip/knee, the walking style is altered, leading to an asymmetric gait. This process possesses the risk of causing long-term effects on walking style, injuring the healthy lower limbs, and force patients to undergo knee/hip prosthesis surgery. To re-learn symmetric walking, the patients with a prosthesis undergo physiotherapy sessions. These sessions aim at recovering the patient's kinaesthetic feedback needed for symmetrical walking. However, these sessions are limited, and more individual efforts need to be invested (i.e., additional time to practice walking). But, unfortunately, the feedback to patients-normally provided by the physiotherapist- is lacking when they want to perform outside therapy sessions. Therefore, the thesis aims to develop a prototype of a wearable device that provides necessary feedback to the user with the correct kinaesthetic feedback to prosthetic joints for symmetrical walking. The choice of a wearable is preferred for the advantages in medical applications and flexibility these devices provide for users. On top of that, the placement of sensors and feedback position will be explored to identify asymmetry walking along with different feedback strategies (audio and haptic) to ensure the best user experience for motor learning.

1.2 Research Questions

The main research question(RQ) of this thesis is:

[RQ] *How to design a wearable that gives haptic feedback for motor learning of patients who undergo hip/knee prosthesis?*

To answer this research question, we need to answer the following sub-questions(SQ):

- [**SQ1**] *What is the state of art in wearables for motor learning using haptic feedback?*
- [**SQ2**] *What gait abnormalities are characteristic for post hip/knee prosthesis patients?*
  - Identification of unique movements present in the gait of the patients with hip/knee prosthesis.
- [**SQ3**] *How to identify the relevant gait pattern?*
  - Placement and type of sensors to be used on the patient's body to observe the unique movements in their walking gait and obtain criteria for asymmetry walking.
- [**SQ4**] *What contributes to wearability for a haptic feedback system?*
  - Position and design of the feedback device that makes it easy to wear, comfortable, and non-intrusive to functionality.
- [**SQ5**] *What is effective and "simple" haptic feedback for gait training (in our case)?*
  - Selecting the right feedback strategy and placement to ensure a smooth experience to the user.

1.3 The Report

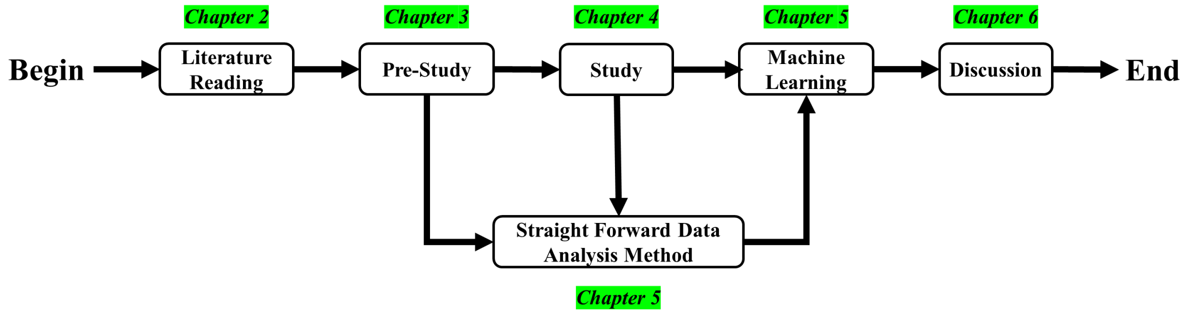


Figure 1.1: Chapter division

This section provides the structure of the report. Fig: 1.1 presents the multiple phases performed for this report. It also offers the progress of this report, with chapter numbers, in gaining the necessary knowledge, observations, and results to answer the RQ. Moreover, the term asymmetric walking refers to the irregularities present in the parameters of the walking activity. In contrast, the term symmetric walking refers to walking where the parameters of the walking activity are normal. The definition of irregularities for asymmetric walking and normal for symmetric walking is dependent on the criteria chosen to address the type of walking activity. Also, the type of walking cannot be labeled to one group of users. For example, an individual can have asymmetric walking due to recent surgery on the knee/hip, but later the same individual can progress to symmetric walking by attending physiotherapy sessions. In this example, it is the same individual with symmetric walking and asymmetric walking. This also indicates that criteria considered to label the walking as asymmetric got improved. Therefore, the sub-research questions (SQ2 and SQ3) focus on determining a criteria/criterion to define irregular and normal parameters present in walking to categorize it as symmetric and asymmetric.

Moreover, the feedback provided to users from the designed wearable device is envisioned to develop the user from the asymmetric style of walking to the symmetric type of walking. However, not every asymmetry is possible to remove from the user. Hence, identifying the possible asymmetries also lies as an area of interest in this thesis. An interview is performed with the physiotherapist to understand these asymmetries [31]. A study is considered to compare users walking without prostheses and users with knee/hip prostheses. The predicted outcome of this study is to identify the asymmetries caused during walking. After establishing the asymmetries, a possible style/method of feedback can be developed to reduce the occurrences of this asymmetry during walking. Moreover, the identification methodology of asymmetry is preferred in real-time rather than post-processing. By identifying the asymmetry in real-time, an opportunity is offered to provide feedback to the user immediately. This type of immediate/concurrent feedback possesses better potential to assist users in their development process. Above all, wearable devices are portable, making it much easier for the user to operate the device more frequently than traditional laboratory-based devices. Moreover, the choice of feedback and feedback location can also impact the effectiveness of the designed wearable device. Therefore, experimentation after exploring the current state of the art is required for the feedback location and style (haptic, audio, etc.).

In chapter 2, the state-of-art and necessary literature will be discussed to understand the possibilities, limitations, and advice required to answer the relevant SQ. In chapter 3, pre-study, a hypothesis is established from the findings in chapter 2 and an interview from the head physiotherapist. Also, the initial attempts of designing a wearable device, sensor position, understanding of the walking patterns by using this wearable device, and development of a real-time algorithm based on the hypothesis (straight forward data analysis method) are made in this chapter. The understanding obtained from this chapter is taken into account for broader study to verify the hypothesis and determine criteria for distinguishing the type of walking. In chapter 4, study, necessary temporary hardware modifications required for the study are explained. With the help of the physiotherapist, this study is conducted on users with hip/knee prostheses. This study involves understanding, determining possible criteria, and verifying the hypothesis for asymmetry from the walking patterns recorded by the users with and without prostheses.

In chapter 5, the development of a real-time algorithm based on the hypothesis and machine learning are explained in detail. The real-time algorithm is developed based on the standard approach of determining asymmetry in walking by verifying criteria (hypothesis in this report). In chapter 6, discussion, the understanding of walking patterns observed from the study and defining criteria for asymmetry are discussed. To conclude, chapter 7, presents the answers for the SQ and future work.

Chapter 2

State of Art & Literature Reading

This chapter will explore the following areas to answer the sub questions(SQ) for the main research question(RQ)

2.1 - Biomechanics of walking/walking gait [SQ2]

2.2 - Kinematics [SQ1][SQ3]

2.3 - Sensors- Position and Processing [SQ1][SQ3]

2.4 - Wearability [SQ1][SQ4]

2.5 - Feedback and Haptics [SQ1][SQ5].

These individual sections targets research sub-questions in a manner providing insights of different authors as part of literature reading. Moreover, an interview with a physiotherapist is completed in search of answers to the sub-questions for the research. Necessary tables are created, to sum up the literature reading of the respective section. Finally, the conclusion (section: 2.6) from the literature reading presents the total idea developed to address/approach the main research question.

2.1 Biomechanics of walking/walking gait

This section is about the characteristics of walking and understanding of gaits. The breakdown of various phases in walking is explored along with different gait patterns, which human beings can develop due to different health conditions. Also, recognizing the physical movements of joints affecting the distinct phases of walking for patients with a prosthesis. An interview with a physiotherapist is equally performed to delve deep into the understanding of walking and possible gait for patients who have undergone prostheses surgery for a knee/hip.

Walking is one of the main and most significant human practices. While the walking stage appears ordinary, this is a dynamic process integrated by the bones, the nervous system (center and peripheral), and the human body's muscles. An individual acquires a distinguished style of walking, called a gait. Gait represents repetitive movements that span both legs, complex muscles, and joints while preserving balance and stability. The quality of human life is assessed by considering the gait of an individual.

The gait estimation is an extensive human walking study [76][77]. To do so, body function, dynamics, and muscle activities are measured by experiments or instrumentation methods. These experiments can be operated to assess, prepare and handle disabled people who impair their walking skills. It is an equally routine approach in sports, for athletics, to help athletes run more effectively and recognize issues in patient posture or activity. Also, kinetics or kinematic study of patient's behavior is monitored with the help of instrumentation of gait analysis. Fig: 2.1 shows different gait cycle phases present in one walking cycle [56].

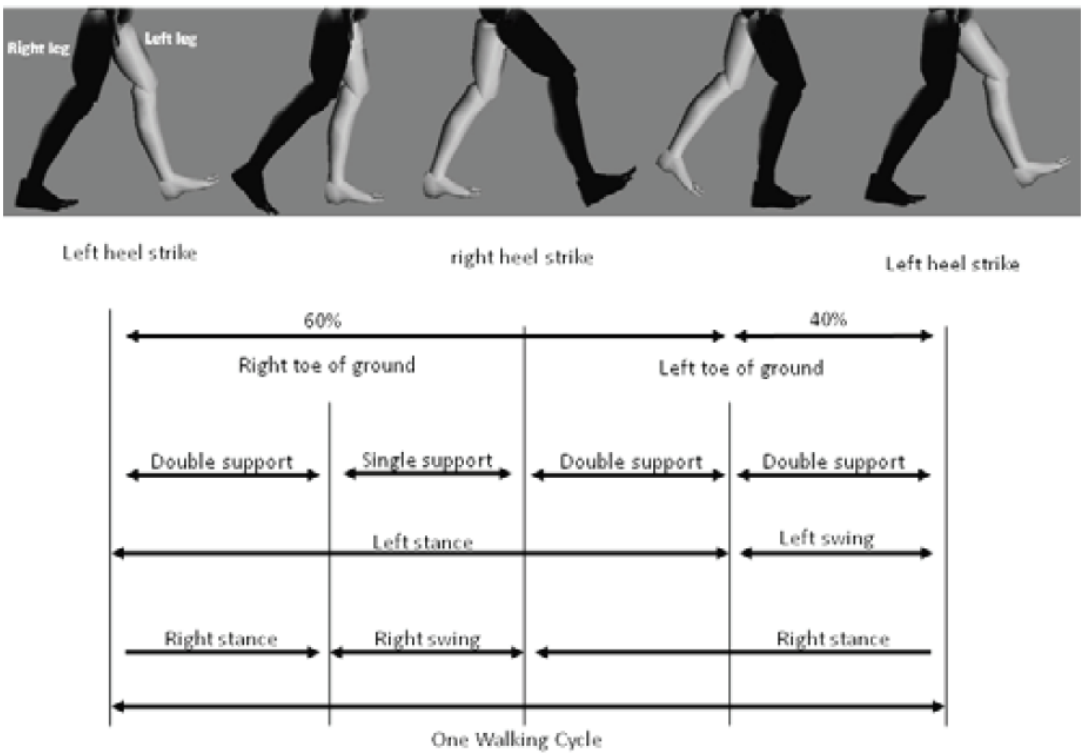


Figure 2.1: Division of gait cycle phases

The walking cycle of one leg is divided into the stance and swing phases (Fig: 2.1). During a walking motion, the center of gravity of the human body is not necessarily on a straight line; it alternately varies on foot stepping on the ground, i.e., right or left leg. This process of foot landing indicates the stance phase, and the remaining action in the walking motion denotes the swing phase. In addition, the walking mechanism on both legs is the same because of the symmetry of the two legs. This resulted in an overlap during their stance phases and called double support. Moreover, the ratio of the stance and swing phase in the standard cases is 6:4 [1].

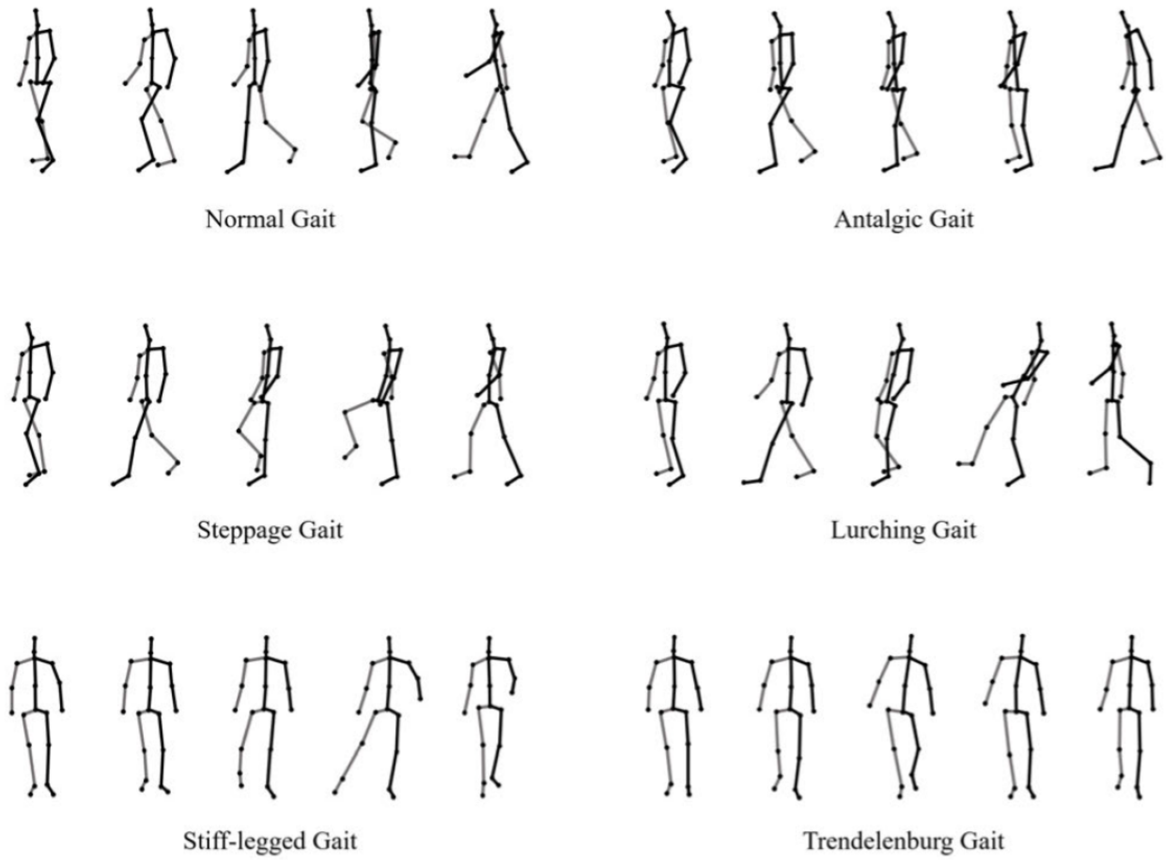


Figure 2.2: Different types of gaits [46]

During an activity, disruption in the mechanical forces in the human body causes an abnormal pattern of biomechanical alignment. These patterns cause impaired movements because of inappropriate assistance (synergistic) and opposing (antagonistic) muscle contractions. Fig: 2.2 showcases the different gaits and Table: 2.1[1] describes the gaits characteristics and causes for the gaits for a human being. These shapes can help recognize vulnerable areas of the body and decide what illness or health conditions a person can suffer from.

[1] *Note: Table reprinted from* [46]

Pathological Gait	**Characteristics**	**Causes**
Antalgic Gait	To prevent pain, trying to bear the weight off the injured leg by shortening the injured leg's stance phase.	Foot, ankle, knee or hip discomfort.
Stiff-legged Gait	While walking, rotating the problematic leg by making an outward semicircle due to stiffness present in that leg.	Rheumatoid arthritis and other joint-related disorders.
Lurching Gait	Weakness of hip extension caused by the injured leg leading to lurching the trunk backward at the heel-strike point in the walking cycle.	The gluteus maximus muscle is weak or paralyzed.
Steppage Gait	The lifting of the problematic leg higher than usual to keep the toes from scrapping the ground due to dorsiflexion problem in the leg.	The anterior tibialis muscle is weak or paralyzed.
Trendelenburg Gait	During stance phase to balance the hip level which lurches the trunk towards the injured leg by moving the problematic hip up and opposite hop down.	The gluteus medius and minimus muscles are weak or paralyzed.

Table 2.1: Gaits Description [46]

During weight-bearing procedures, knee joint loading is most extensive and also potentially detrimental to the knee. Especially when walking, the joint loading of the knees are of concern because walking is the most normal means of human locomotorisation and causes repeated joint actions. There is increasing agreement that knee osteoarthritis (OA) is biomechanically driven [78][4][16] and caused by aberrations in the biomechanics of the knee [27][5]. The focal point of the biomechanical factors for the disease's start and development is that joint loads and joint loadings are widely agreed upon for knee OA's pathogenesis [48][49][4][16][27][5].

Gait variations are primarily found in the frontal plane between knee OA patients with medial knee OA and control subjects. This included declining internal hip abduction moments during the stance stage, which may result in a Trendelenburg gait[2] which results in a greater peak for external knee adduction moments for the knee OA patients, especially patients with an extreme knee OA [49].

Moreover, the research performed by the authors [74] illustrated that kinematic data (spatiotemporal parameters) resulted in indicating that the swing phase duration of the prosthetic limb increases and stance phase duration of the intact limb increases. This observation is recorded because the person tends to stand longer on their healthy limb rather than their limb with a prosthetic. The adaptation of the prosthesis limb during the stance phase increases the muscle work of the hip-extensors and ankle-foot plantar flexors. This is performed to compensate for the less performing limb. Furthermore, the body center of mass will rise allowing the prosthesis limb from the ground during the stance phase [60]. Now, during the stance phase, the inability of the prosthesis limb in certain movements leads to more wore than usual for the healthy limbs [60].

[2] $https://www.physio-pedia.com/Trendelenburg_Gait$

2.1.1 Interview with physiotherapist

An interview with a physiotherapist [31] provided more practical insights into arthrosis in the hip/knee for an individual. The interview is summarized into two sections, 'Before Surgery' and 'After Surgery,' to realize the factors and procedure involved.

Before Surgery:

- Due to damage (arthrosis) in bones/joints (hip/knee) present for the user, which forces to change the user walking style to a different walking style, i.e., symmetric to asymmetric. The user developed this change in walking style to comfort/reduce the pain generated during symmetric walking.
- The common asymmetric walking gait observed in those users is Trendelenburg Gait

After Surgery:

- The damaged joint is substituted by a prosthesis, but the strength of the muscle connected cannot be regained immediately to move the leg like before surgery. Therefore, several exercises are practiced by the user with the help of a physiotherapist to strengthen the muscle.
- In general, if a user undergoes a hip/knee surgery on the right side of the leg, then the pelvic drop can be observed on the left side while walking and vice versa. This drop indicates that the user is avoiding/restricting the leg movement on the operated side of the leg.
- However, even after the muscle regained its strength, the user's walking pattern can still be similar to one before the surgery (asymmetric walking), which the user-developed due to pain.
- Hence, the physiotherapist also helps change this asymmetric walking to symmetric walking by providing feedback, e.g., by giving rhythm by clapping or placing hands on the user's hip while practicing walking. This feedback is provided especially on hips to the user to ensure symmetric walking.
- The frequency and duration of these practice sessions with the help of a physiotherapist varies according to the individual user. In addition, users will be requested to follow some exercises to practice at home also.

Besides, according to the physiotherapist, the footstep duration of these patients varies from the healthy person's footstep duration. This behavior occurs because of the reduction of functionality in the damaged leg. Moreover, the footstep duration will also vary for the same user when compared with the healthy leg. This action can be exploited to identify asymmetry in walking, and appropriate feedback to users can avoid this practice of asymmetry walking.

2.2 Kinematics

This section is about various kinematics parameters derived from a gait, understanding different intermediate parameters present in walking phases, and kinematics analysis for the same. Also, exploring distinct approaches by multiple authors to derive the kinematic parameters addressing the intermediate walking phase conditions.

Kinematics is the science of motion. In human movement, it is the study of the positions, angles, velocities, and accelerations of body segments and joints during motion. The foot, shank (leg), thigh, pelvis, thorax, hand, forearm, upper-arm, and head are considered to be rigid bodies for describing the locomotion of the body (Fig: 2.3).

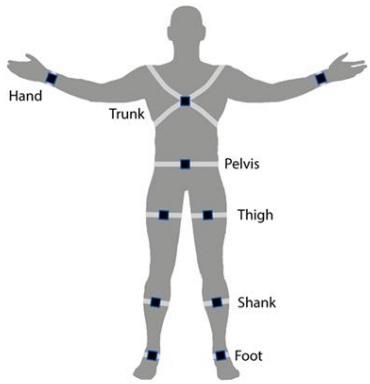


Figure 2.3: Rigid Bodies

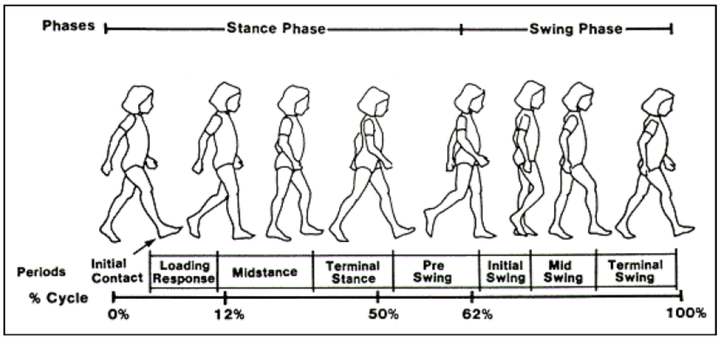


Figure 2.4: Gait cycle

The authors [62] originally described six major determinants of gait - pelvic rotation and obliquity, stance knee flexion, foot and ankle mechanisms, and tibiofemoral angle- as precise movements by stance lower limb that theoretically minimized vertical excursion of the body's center of mass (CoM). These factors establishing the measurable position of the center of gravity of the body were completely derived from kinematic considerations. A smooth sinusoidal trajectory is produced due to shifting in body's center of mass in differing symmetries, which is caused by the displacement of the pelvic list and rotation, posture knee flexion expansion, foot and knee interaction, and lateral pelvic. In addition, this association triggers the velocity and accelerations of the whole body to undergo a cyclic fluctuation.

These variations in velocities and accelerations are exploited for various activities that involve the locomotion of the body. Based on the operations, various solutions are derived by different authors trying to present efficient solutions. These solutions targeted focused on identifying different phases in the gait cycle, i.e., stance & swing phase (Fig: 2.5, 2.4). Besides, intermediate parameters of stance phase are analyzed - Heel-Strike(HS), Foot-Flat(FF), Heel-Off(HO), and Toe-Off(TO) (Fig: 2.6)- intensively to identify different gaits.

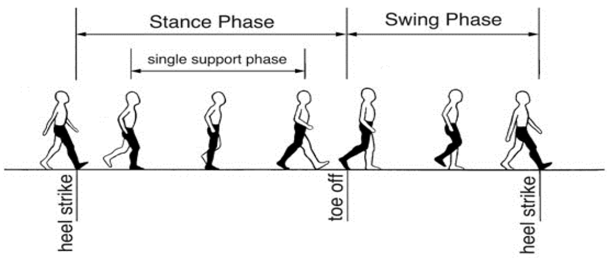


Figure 2.5: Indication of Heel-strike & Toe-off in Gait cycle [71]

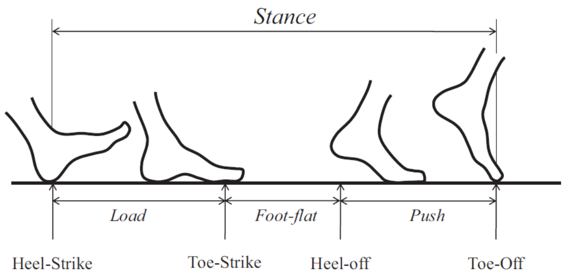


Figure 2.6: Temporal events during Stance and corresponding inner-stance phases (in italic). [41]

The gait parameters behavior for every activity varies for both healthy people and unhealthy people. The authors [63][54][45] focused on identifying gait phases by using different algorithms and approaches based on sensor positions, types, and several sensors (more about this in section 2.3). Also, the authors [26][45][61][11][47][53] proposed methods or mathematical models representing different stances of gait targeted at determining various angles and speeds in lower limbs. The authors [55][29] focused on identifying the measurements recorded by sensors (patterns) to determine different gaits. The authors [29] implemented 4-layer GRU (Gait Recurrent Unit) neural networks with 125 hidden neurons in each network. Moreover, the authors of [13] implemented machine learning algorithms based on the features obtained from the mathematical model developed to test their performance in regression. Learning algorithms like Naïve Bayesian (Bayes), Random Forest (Bagged Tree), Multivariate Adaptive Spline Fitting (MARS), Multilinear Regression (MLR), and KNearest Neighbors (KNN) are used to compare feature performance.

The authors [72][71][11][47] used another approach to calculate walking parameters like walking speed, stride period, and walking distance parameters. They try exploiting the step period and stride length as these conditions differ in healthy and unhealthy human walking. In a healthy person, the walking speed is higher, which leads to stride becoming larger and the period of a step becomes shorter. By doing this, the authors' goals are to distinguish between a healthy and unhealthy person. This process is complex because measurements of these parameters vary from person to person. This procedure depends on spatiotemporal parameters, which are derived from the foot during the stance phase of the walking gait. There are mathematical calculations/approaches for these parameters which provide the walking parameters. However, these calculations are strongly dependent on sensor measurements which are tightly linked with the position of the sensor. This results in numerous calculations which differ for sensors position. To differentiate these parameters in one cycle of walking, the signal patterns of the swing phase and heel-strike phase are considered as references. Table: 2.2 illustrates few examples of different processes implemented by various authors to calculate the parameters of kinematics.

Ref	**Application**	**Processing/Method**	**Real-Time**
[20]	Rock Climbing	After calibration, calculation of two thresholds for the measured mean pressures for 30sec and 20sec respectively and relevant feedback(vibrations) are set.	Yes
[25]	Running	Calibration - Resistive values of FSR change according to persons weight, Defined 3 states (i) In Air (ii) Landing (iii) Taking Off Evaluation - Heel strike detection (On- Landing state) & threshold determination	Yes
[22]	Running	Static User Calibration - Estimate the orientation of the accelerometers in the body reference frame Online Calibration Refinement - Updating the reference frame after the user starts to run Evaluation - Custom designed transfer function	Yes
[36]	Walking	Calibration - Static orientation for all 3 orthogonal vectors in alignment with gravity Observation - Acceleration waveform contains rhythmic patterns of gait Quantified gait parameters - Mean, the standard deviation for acceleration	No
[63]	Walking	Process - Angular information from gyroscope and accelerometer and conversion of rad/s values to deg/s Evaluation - Calculation of Yaw, Pitch, Roll by formula mentioned in the paper	No
[54]	Walking	Process - Values of accelerometer & gyroscope are processed through Kalman algorithm Evaluation - Combination of FSR sensor values and processed output from Kalman algorithm resulted in determining swing and stance phase	No
[26]	Walking	Process - Considering about one cycle of one leg, knee angle dynamics model, knee angle & hip angle estimation are done	No
[55]	Hemiplegic Walking	Observation - Measured gait signals show a specific pattern for walking	No
[45]	Walking - Foot Drop	Evaluation - Gait phases are determined using Bayesian formulation with a sequential analysis method & ankle angle measurement Observation - Detection of heel-strike & toe-off illustrated good agreement	No
[50]	Walking	Process - The subjects were asked to stand still for one minute before waking. The sensors information are transmitted wireless to a laptop for post-processing using Wavelet Principle Component Analysis Observation - The measurements made from the accelerometers and gyroscopes are identical, especially for the heel-strike in stance phase	No

Table 2.2: Summary - Methods

2.3 Sensors - Position and Processing

This section explains the advantages of inertial measurement systems over the fixed measurement systems for designing wearables and performing kinematic analysis for various activities. In addition, presenting different locations on human bodies, these sensors are placed for performing analysis performed by multiple authors. Also, methods/techniques are implemented to reduce noise or increase the quality of the information obtained from the sensors to perform real-time/post-processing.

To perform movement/gait/kinematic analysis of different gaits performed by human beings, in general, there are two approaches based on the technology and measurements involved (i) Fixed Capturing systems and (ii) Inertial Measurement systems. Plus, there are electrogoniometers, electromyography (EMG), and metabolic energy expenditure approaches, which are restricted to the confines of a clinical environment [17][37][42]. Fixed Capturing systems involve the usage of motion capture devices like cameras (motion capture), Kinect, and force platforms. Whereas, Inertial Measurement systems primarily use gyroscope and accelerometer sensors to perform movement analysis. Therefore, establishing these types of sensors suitable for wearable devices. Table: 2.3 illustrates different categories of sensors used in the kinematic analysis.

Sno	**Measurement Categories**	**Properties**
1	Motion Analysis	Pictures that can record movements of the whole body. Often used to evaluate magnitude and timing of individual joint movement
2	Electromyography	Record indirect identification of period and the relative intensity of muscle function
3	Force Plates	Record ground reaction forces (GRF) generated as the bodyweight drops onto and moves across on the supporting foot. The force plates are often used in combination with camera systems
4	Body fixed sensors (accelerometers & gyroscopes)	Record energy cost during gait and/or segmental accelerations during walking

Table 2.3: Sensor setup Categories

In recent years, these Inertial Measurement devices have been utilized to classify the gait cycle because they are less expensive than camera-based setups, compact, and simple to mount, as opposed to camera-based systems, which require a dedicated arrangement (i.e., location markers on the subject's body and room). Furthermore, because of its sheer weight, low power consumption, and less susceptibility to environmental conditions, inertial sensor technology is being more generally used in medical wireless applications. On top of that, these inertial measurement instruments have steady measurement precision in terms of Spatiotemporal parameters, as well as higher efficiency and realistic gait measurement [14][73]. However, they are prone to error that accumulates over time, also known as "drift". These devices constantly round off small fractions in their calculations which accumulate over time and can add up to significant errors in measurements. But, these errors are reduced with the help of corrective methods/algorithms. To highlight the more advantages of wearable sensors (Inertial Measurements Systems) over the current laboratory systems (Fixed Capturing systems), Table: 2.4 [3] compares the laboratory gait analysis tools and their wearable counterparts.

	A **Conventional**	*A* **Wearable**	*B* **Conventional**	*B* **Wearable**	*Muscle Activity* **Portable**
Instrument Type	Optical Motion Capture	Inertial Sensors	Force Plates	Insole Pressure Sensors	EMGs
Practicality	Pre-installation and expert operation	Easy to wear	Pre-installation	Easy to wear	Cumbersome or invasive to wear
System Cost	$> \$30000$	$< \$2000$	$\$200 \sim \$3000$	$\sim \$3000$	$\sim \$10000$ (wireless)
Continuous Monitoring	$< 10minutes$	$> 2hours$	$< 10minutes$	$> 2hours$	In-lab & out-of-lab
Accuracy & Precision	High	Sensor/Algorithm dependent	High	Sensor /Algorithm dependent	The only type of instrument for muscle activity
Measures	Kinematic measures	Capable of emulating optical motion capture	Kinetic measures	Capable of emulating force plates	Muscle activities and kinetic measures
Computation Cost	High (computing coordinate triangulation)	Low	Low	Low	Low
Real-time Potential	Limited	Implemented in Research	Limited	Yes	Yes

Table 2.4: Current Quantitative Measuring Instruments For Gait Analysis [12], *Column A* - Kinematic Information & *Column B* - Kinetic Information

Table: 2.5 presents the different positions of the sensors placed by authors [20][22][25][36][63][54][26][55][45][50] on the human body for different activities. The most common sensor placement (accelerometer & gyroscope) on the body for locomotion is done at the knee, thigh, shank, foot, and waist (L3 & L4 spinal segment). These sensors are popularly situated on the human body using elastic bands and housing. However, the authors [22] designed wearable shorts that carry sensors, wiring, and processing unit. This choice is driven by the activity implementation (running). The authors [20] designed a pouch for holding the sensors which were attached to the shoe, and this idea was followed based on the activity (rock climbing) and users comfort. Now coming to the pressure sensors, used in combination with accelerometers & gyroscopes for walking, are located on the sole of the shoe, which is the ideal location to measure the kinetic information. The authors [20][25][54][26][55][50] used the pressure sensors in combination with the inertial measurement sensors for different activities. The measurement readings of the pressure sensor are often considered for identifying the different walking phases, i.e., the pressure sensor activates during the stance phase and remains inactive during the swing phase.

The measurements of the signals from accelerometers and gyroscopes are majorly recorded at 200Hz by many authors. These recordings are either directly recorded by the processing unit present with the sensors or transmitted via wireless to another device for recording, and then post-processing is done on those signals. Moreover, the signals from these sensors are considered to be noisy, and many processing techniques are followed by the authors. Methods like Butterworth filter, Kalman filter [54], and principle component analysis (PCA) [50] are implemented to smoothen the signals for main algorithms

[3] *Note: Table reprinted from* [12]

to make the decision. Furthermore, there are custom calibration methods/procedures followed by different authors to establish a reference to perform their algorithms for real-time or post-processing. The technique of post-processing is implemented by the authors, [36][63][54][26][55][45][50] especially for the walking activity, which eliminates the concept of real-time feedback to users (Table: 2.5). The authors [22][20][25] have implemented real-time feedback by implemented custom transfer functions and threshold conditions based on the activity. Table: 2.2 summarizes the above-mentioned processing methods and real-time feedback.

Ref	**Application**	**Sensor Position & Type**	**Real-Time Feedback**
[20]	Rock Climbing	Shoe insole - Pressure sensitive foil (Velostat) Top of shoe - LilyPad Accelerometer & Arduino	Yes - Vibration motors Location - Fibula & Tibia
[25]	Running	Shoe insole - Force Sensing Resistor (FSR)	Yes - Electrical Muscle Simulation (EMS) Location - Calf Muscle
[22]	Running	Knee - Accelerometer (ADXL330)	Yes - Vibration motors (Rumble feedback) Location - knee
[36]	Walking	Lateral malleolus & parallel to tibia - Accelerometer (ipod)	No
[63]	Walking	Feet, Tibia, Thigh, Umbilical - Gyroscopes & Accelerometers (MPU-6050)	No
[54]	Walking	Tibia - Gyroscope (ADXRS610) & Accelerometer (ADXL203) Foot - Force-Sensitive Resistor (FSR)	No
[26]	Walking	Waist, Thigh - Accelerometer (MMA7360L) Feet - On/Off compression type switch sensor	No
[55]	Hemiplegic Walking	L3 & L4 spinal segment - Accelerometer (MPU-9250) Feet - Capacitive insole force sensor	No
[45]	Walking - Foot Drop	Shank & Foot - Gyroscope & Accelerometer (Trigno IM)	No
[50]	Walking	Foot - Gyroscope & Accelerometer Sole - Pressure sensors	No

Table 2.5: Summary - Sensors and Feedback

2.4 Wearability

This section concentrates on wearables design, functioning, and ergonomic disciplines followed in wearables. Also, understanding the role and adoption of wearables in various activities, especially in sports. Moreover, getting to identify the approaches for understanding and increasing the acceptance conditions for wearable devices.

Wearables exist on people's bodies, as compared with other electronic devices, including computers and smartphones. This fact implies a significant shift in wearables design and working. The varied consumers and their cultures necessitate considering the design process of wearables like procedures, ingredients, and distinct concepts comprising textiles, electronics, and software [18]. As a result, achieving wearable usability success is no longer about achieving technological success but rather about achieving the best possible user experience [10].

In recent years, many authors explored diverse aspects of wearables to assessing their role in various activities. The physiological energy expenditure, biomechanical effects, discomfort due to musculoskeletal loading, and perceptions of wellbeing parameters are assessed by the authors [33]. Other authors focused on the importance of the psycho-physical well-being of users [9] and to adopt a human-centered approach to develop the wearables more practical, stable, secure, and appealing [15]. A user-centered approach to wearables research involves a wide variety of choices. Besides, the importance of using a non-intrusive control model is emphasized by authors [2], in terms of data privacy to avoid impacting consumer habits and routine activities.

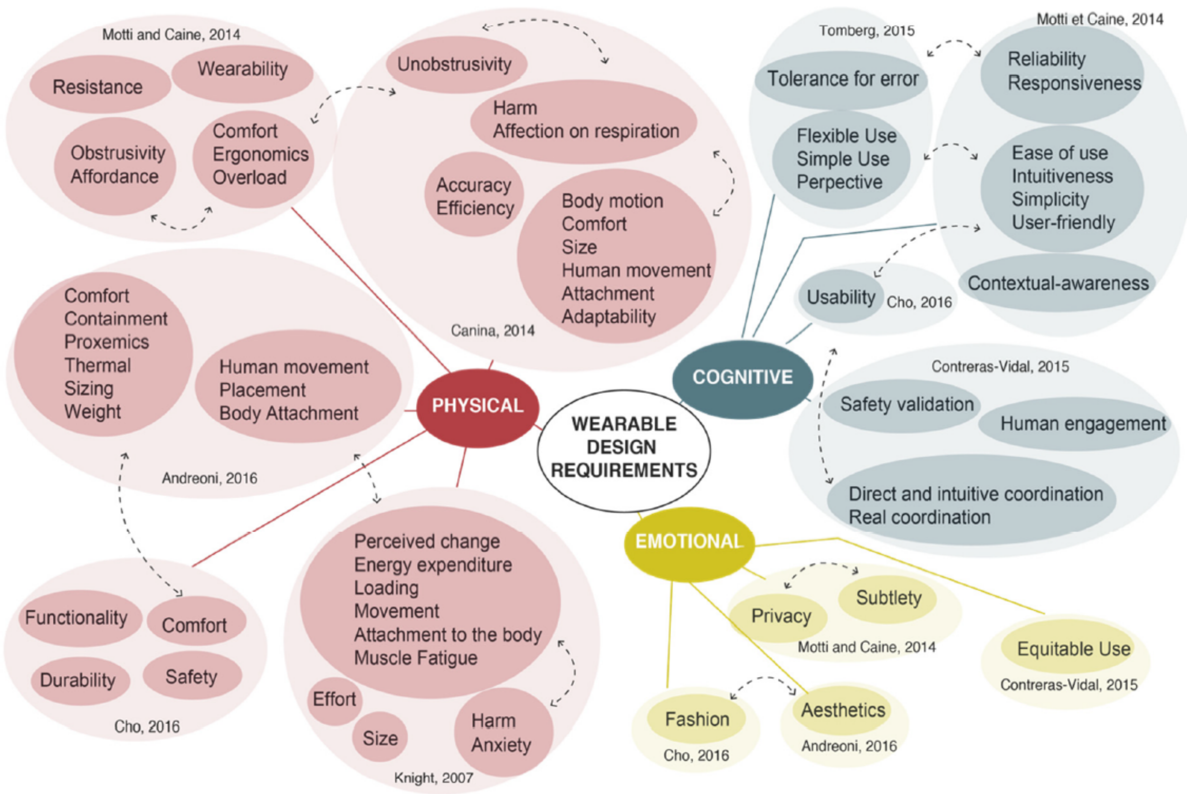


Figure 2.7: Ergonomics Disciplines [3]

The survey paper by authors [3] designed a mind map illustrating all the design requirements proposed by numerous authors categorized into three key ergonomic disciplines - physical, cognitive, and emotional (Fig: 2.7). They extended these ergonomic disciplines to respective sub-design requirements: safety, comfort, durability, usability, reliability, engagement, and aesthetics, to categorize the design requirements to be studied for wearables. The Fig: 2.8 depicted by the authors survey demonstrates the specific conditions to be taken care of under each sub-design requirement. Besides, the mind map showcases authors whose design requirements do not involve all the three disciplines and focus more on one ergonomic, primarily physical ergonomic.

Figure 2.8: Wearable design requirements [3]

Another group of authors surveyed the trends and opportunities in Human-Computer Interaction (HCI) for design aspects of wearable systems in sports [44]. They categorized the varied perspectives from multiple authors: tech-driven, design, and acceptance. The tech-driven concentrates on novel devices used in specific sports (tennis, rowing, rock climbing, swimming, basketball), the design focuses on design aspects (designing workshops, interviews with potential users, online review, questionnaires), and acceptance focuses on large user studies investigating the acceptability of devices (in-depth interviews, online surveys, logs, sentiment analysis, auto-ethnography). Primarily for sports, physical, cognitive-emotional, and social aspects are distinguished to investigate the role of wearables in sports. The author [81] summarized the body regions suitable for placing wearables (Fig: 2.9), and movement sensing (Fig: 2.10). These regions match the authors (mentioned in Table: 2.5) work for measuring and designing a wearable device. Overall, the wearables are worn more often when socially accepted, non-intrusive, acceptable, and many more as there is no standard solution for this. However, following the design requirements satisfying the ergonomic disciplines can better acceptability to a user without jeopardizing the wearable device's functioning.

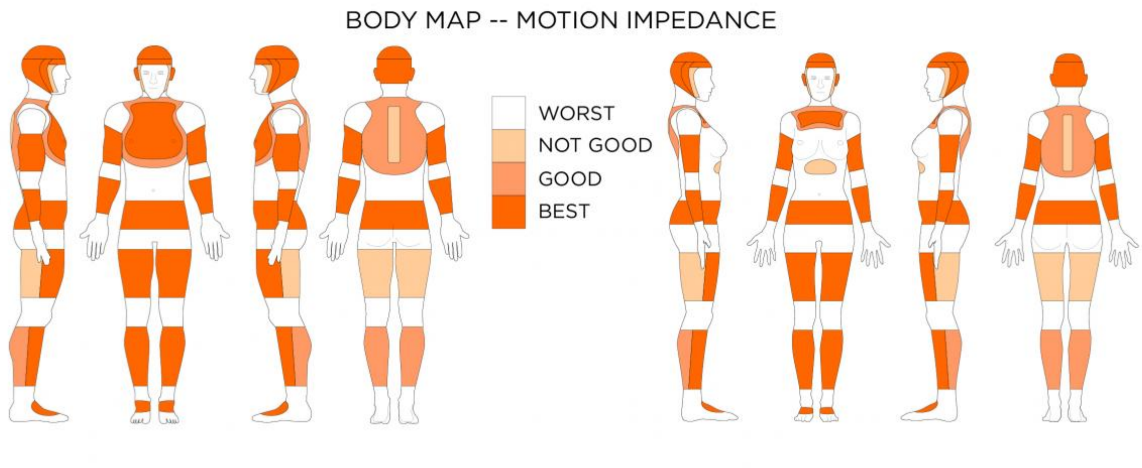


Figure 2.9: Body regions suitable for placing wearables [81]©

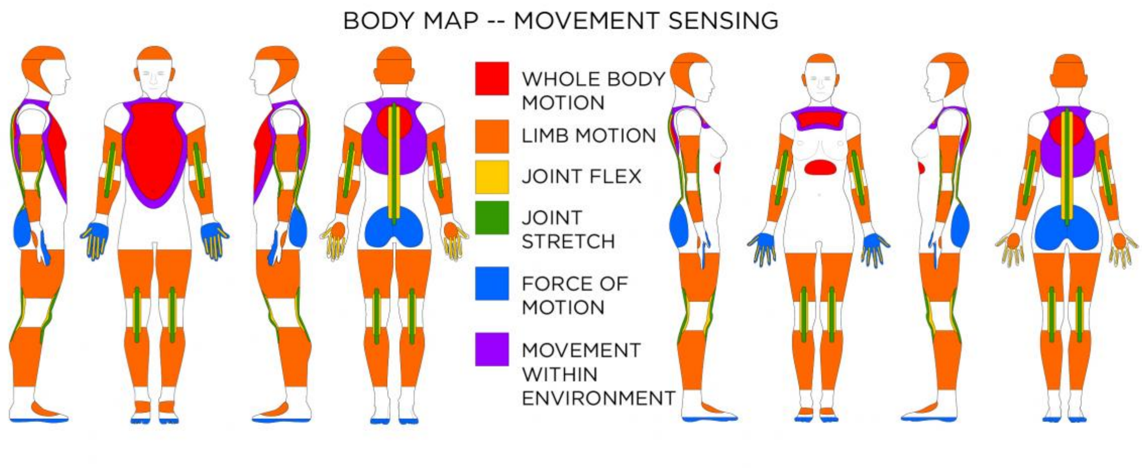


Figure 2.10: Movement sensing [81]©

2.5 Feedback and Haptics

This section is about the feedback strategies used for motor learning. Also, learning various methods of feedback investigated by multiple authors for different activities. The influence of concurrent feedback strategies for motor relearning is also observed for haptic feedback. Besides, understanding possible advantages for kinaesthetic feedback using the haptics strategy already implemented for sports activities.

Feedback is considered a key variable for the acquisition of skills and is widely characterized as any sensory information involving a response or movement in motor learning. There are two types of feedback strategies (i) Concurrent feedback and (ii) Terminal feedback. These strategies are classified based on the point in time at which feedback is provided. In the concurrent feedback strategy, the feedback is provided during motor task execution, whereas the feedback is provided after motor task execution for the terminal feedback strategy. Depending on the activity and requirement, the feedback strategy is selected. In general, there are visual, audio, haptic, multimodal types of concurrent feedback. The authors [65] illustrated the effectiveness of a feedback strategy for motor learning based on the complexity of the activity/functionality Fig: 2.11.

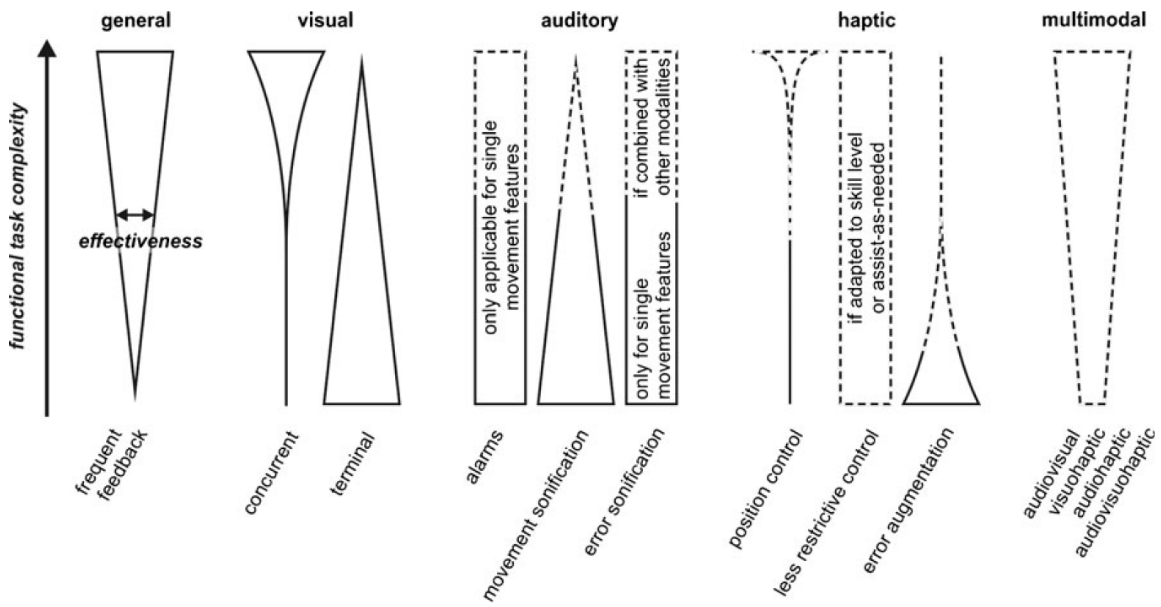


Figure 2.11: The figure shows the experimentally confirmed (solid) and our hypothesized (dashed) effectiveness of a feedback strategy to enhance motor learning depending on functional task complexity. The broader the shape, the more effective the strategy is [65]

The walking activity is considered as a complex task according to the task complexity defined by authors [79]: "We will judge tasks to be complex if they generally cannot be mastered in a single session, have several degrees of freedom, and perhaps tend to be ecologically valid. Tasks will be judged as simple if they have only one degree of freedom, can be mastered in a single practice session, and appear to be artificial". In general, a patient seems to benefit more from concurrent feedback as the job becomes more complex. The possible reasons for this, according to the same authors, are (i) concurrent feedback to be beneficial for motor learning since it develops automaticity in movement control (ii) concurrent feedback in the early stages of learning prevents cognitive overload. These observations comply with the feedback practices followed by physiotherapists in the rehabilitation centers (section: Interview with physiotherapist). Thus demonstrating a possibility for examining the existing feedback strategy for a wearable device.

Visual Feedback	**Auditory Feedback**	**Haptics Feedback**
Types:	**Types:**	**Types:**
(i) Simple Tasks: Simple labor tasks E.g. simple lever arm movement (ii) Complex Tasks: Practice of complex mobilization skills E.g. 90° interlimb out-of-phase coordination task	(i) Auditory Alarms: A sound is played without modulation (ii) Sonification of movement variables: Non-speaking audio representing magnitudes and shifts overtime. (iii) Sonification of movement error: When the output of the target and actual variables deviate from each other.	(i) Position control based haptic guidance: Most restrictive place and time haptic guidance. (ii) Haptic guidance beyond position control: With the deviation from the reference trajectory the correction force increases. (iii) Vibrotactile feedback: Vibrotactile displays have been designed to enhance navigation and orientation to minimize visual and auditory system workload.
Design Aspects:	**Design Aspects:**	**Design Aspects:**
(i) Abstract visualizations: The variable of tasks is depicted as lines, curves, gauges, bars, or points on a basic display. (ii) Natural visualizations: Integrating 3-D views of a reference or of the corresponding portion of the user.	(i) Parameters: Loudness, pitch, timbre combined with auditory feedback (ii) Auditory display : Pitch height varies w.r.t. numeric values, time information by rhythmic patterning of a pitch-mapped stream, and primary occurrences through volume shifts.	There are no generic design aspects due to its tightly bound nature for implementation requirements which depends on the application domain
Overall:	**Overall:**	**Overall:**
Concurrent visual feedback improved acquisition performance, but not retentions testing. It was proposed that the participant could easily access the brief details of the complex task.	Concurrent auditory feedback was used in motor learning successfully. Auditory features can prevent the other sensory afferences to a far smaller degree in contrast with visual input.	The most fundamental method of haptic augmented feedback is position management techniques. They seem useful in motor (re-)learning, especially in patients, because of the motivational component offered by successful task completion and improved training time and strength.

Table 2.6: Summary - Concurrent Feedback strategies [65]

Table: 2.6 outlines the key aspects of the concurrent feedback strategy of the survey paper written by authors [65]. This table distinguishes the essence of different strategies present in concurrent feedback. Among the various strategies, the haptic guidance with position control strategy, which utilizes a haptic interface to direct the human subject through the perfect action, makes it more suitable for motor re-learning. This strategy provides a correcting force that pushes the user's limb toward a physiological reference trajectory or posture, i.e. when there is a deviation from the reference trajectory, the correcting force increases. Also, it increases the effectiveness of relearning a motor skill through kinaesthetic feedback. The haptic sense also enables users to engage with and interpret connections/experiences with the world around them. Besides, this singular feature refers to the haptic sense's bidirectional property, which provides the foundation for increasing motor learning through haptic experiences. [65].

According to the authors [39], haptic feedback guidance may lead to muscle and connective tissue strengthening by inducing motor plasticity and avoiding stiffness. This is achieved by reinforcing the body movement by performing the same repetitive movements. Moreover, physiotherapists are relieved of back-breaking duties, allowing them for further preparation and improving morale as a result of completing an active challenge. The authors [22][20][25][58][40] have used haptics feedback in sports to assist users for better motor learning of the respective sport. This feedback may help beginners to learn complex sports movements in a safe and self-explanatory manner. The authors [22][25] implemented the concurrent feedback strategy using haptics for the running sport. They assist/guide the runner based on the sensor's information and provide concurrent feedback to control the movements made by the users. However, as of the knowledge/scope of this report, a similar implementation of concurrent feedback for walking is not carried out.

2.6 Conclusions

For the state-of-the-art in wearables for motor learning using haptics feedback [SQ1], there are many implementations and methods developed for activities majorly in sports like tennis, rowing, skating, running, rock-climbing, swimming, and few authors for walking. However, these authors who focused on walking, identify various gaits of walking using different approaches, but they implemented their idea using post-processing. By performing this, they eliminated the idea of real-time feedback to the user. Though the sensors suitable for wearables are used, they only transmit the information to a host computer for analysis. Therefore, this concludes from sections 2.2, 2.3, 2.4, and 2.5 that a creative method or fusion of methods to be implemented to design a wearable for motor learning for walking. Hence, more focus can be shifted towards the work produced by authors for the sport running because of few similarities in sensing and body movements.

Based on the review of the literature and the interview done with a physiotherapist, the general symmetry and asymmetry of walking can be distinguished for patients with hip/knee prostheses by basing on [SQ2]: the parameters in the stance phase (step duration) and specific body part movement which depends on the type of gait which the user developed. For example, in Trendelenburg's gait, the healthy leg side pelvis of the patient shifts downwards because of the unhealthy leg. This results in different step duration for each leg for the same user. Furthermore, the time duration for the stance phase and swing phase by patients with prosthesis limbs varies when compared with a healthy person. This behavior can also be experimented with, knowing the time for one step taken by symmetric walking is 1-second [75]. Therefore, this concludes that the above-mentioned characteristics (Summarized from the section 2.1) can be utilized for identifying the asymmetries in walking for the patients with hip/knee prostheses.

The kinematics analysis approach/methods of the walking gait can be focused on the stance phase [SQ3]. By performing this, the determination of the step duration can be measured smoothly. The inertial measurement sensors can be used for this approach as the Spatio-temporal values obtained from these measurements are accurate/similar for the stance phase when compared with the exo-skeleton setup by the authors [50]. Furthermore, the placement of the sensors on the body can be narrowed down to the shank, lower back, and foot. The authors [82] result from their experiments, to identify the gait symmetry based on the diverse location of the sensors, demonstrated that the measurements collected from the lower back and foot sensors perform identically. However, the sensors positioned in the foot showcased an easier identification of symmetry and asymmetry than sensors positioned on the lower back.

Therefore, the conclusion from the preceding paragraph (Summarized from section 2.2 and 2.3), the identification of stance phase parameters like heel-strike and toe-off will be an indeed good beginning point in coming up with a creative method to identify varying types of walking. From these parameters, we can determine the frequency of this occurrence in walking cycles which can be used for threshold conditions or for the algorithm in determining step duration. For validation of these parameters, pressure sensors on foot can be used to confirm the right instance of these parameter occurrences. Nevertheless, keeping in mind that different sensor positions can make this determination easy or difficult. To begin with, sensors positioned on the lower back and foot can be a good initiation point when compared with the behavior of the signals from the post-processing work performed by the authors mentioned in the 2.2 section.

The feedback and wearability for the user to indicate symmetric and asymmetric walking leaves more room for experimentation [SQ4][SQ5]. This is due to the lack of previous work, which showcased no similar use case. However, a few similar sports involving lower limb activities like running and rock climbing can be considered as a beginning point for experimentation because the concurrent feedback is implemented with haptics in these sports. However, the type of feedback strategy is also left to experimentation where concurrent feedback strategies like haptics and multi-modal (audio and haptics) show an appropriate opening point for experimentation. This includes acknowledging the user's acceptability and ergonomics disciplines of the design requirements along with the type of feedback to equal measures. Therefore, this concludes that (Summarized from section 2.4 and 2.5) an experimental wearable device and feedback strategy needed to be developed to address the kinaesthetic feedback for the prostheses present in the patient's joints.

For experimentation of wearability and feedback, the questionnaire method with suitable candidates along with the physiotherapist feedback can be used. This can ensure a safe design of a wearable prototype and determining the effective location on the human body for providing the feedback to assist the motor relearning. In this process, multiple ideas for various ergonomics can be examined to get better acceptance from users. The same can be done with the feedback strategy; the physiotherapist insights plus survey with users can result in a strategy that assists the user for better motor relearning.

To conclude, the sub-questions for this thesis targetting the state-of-art [SQ1], characteristics of asymmetry walking [SQ2], and identifying asymmetry patterns in gait [SQ3] resulted in acceptable content/ideas answering them. However, regarding the wearability [SQ4] and feedback strategy [SQ5] questions, there is no relevant previous work to answer these questions immediately. Hence, more experimentation is required to answer these questions.

Chapter 3

Pre-Study

This chapter features the attempts in earlier stages-first and second development - of the thesis to understand the various criteria/patterns to distinguish the symmetric and asymmetric walking. Moreover, the device (used to collect the IMU signal measurements/patterns) construction and development process are presented in this chapter. In addition, the parameters and location of the sensors on the human body are established. All the choices/parameters were selected to ensure the functionality (capable of distinguishing symmetric and asymmetric walking) and users comfort when using the designed wearable device (number of sensors, location, and non-intrusive to walking activity). After the conclusions from the literature reading from chapter 2, the following hypothesis is derived for criteria (for this report) to define asymmetric walking:

Hypothesis: *The intermediate step duration differs significantly for the users with a prosthesis in the hip/leg in comparison to the users without a prosthesis.*

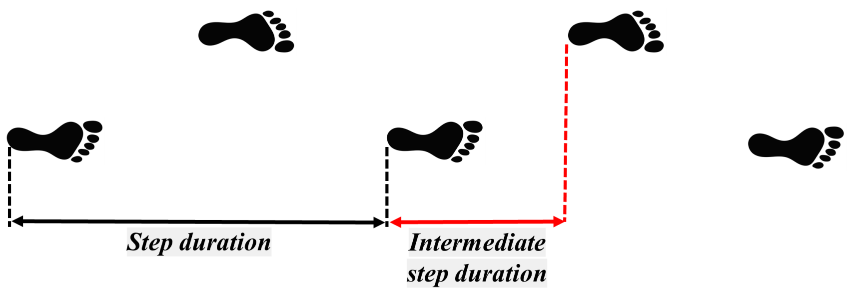


Figure 3.1: Step duration and intermediate step duration

Fig: 3.1 assists in understanding the difference in step duration and intermediate step duration used for defining hypothesis. To verify the hypothesis, to begin with, obtaining the walking patterns and understanding of them is required. Secondly, to verify with bigger sample size (participants) of real-time walking data of users with and without prosthesis to verify intermediate step duration. Thirdly, in parallel with second, developing an algorithm to identify the heel-strike events or possible triggers to determine the intermediate step duration from the recorded walking patterns. Altogether, each step is performed to ensure that all the operations required to determine the intermediate step duration are feasible in real-time processing.

3.1 First Development

From the Chapter 2 conclusions, the lower back location showcased a promising outcome because only one IMU is required to record both legs stance and swing phases. This location equally fits into the good design choices for wearable devices because the device location on the human body is non-intrusive to human activities. Therefore, the MPU6050 6-axis IMU sensor (Fig: 3.2) positioned on lower back (Fig: 3.3(b)) is used for measuring the amount of linear accelerations (m/s^2) and angular ($°/s$) velocities patterns generated during walking with the orientation shown in Fig: 3.3(a), (c). This sensor position and orientation are considered the default arrangement for the rest of the report, i.e., the recordings of the IMU sensor are measured by this arrangement. If any other sensor location or orientation is used for measurements, it will be mentioned explicitly in the remainder of the report. According to the sensor location and orientation (Fig: 3.3), the accelerations measured along the Y-axis suggest the ground impact of the left and right feet while walking. At the same time, the accelerations measured along the Z-axis indicate the forward motion caused while walking. Besides, the angular velocities measured by the gyroscope along the Z-axis, and X-axis points to the pelvis movement which is caused by the hips motion during walking. All the statements mentioned above are strictly applicable because of the sensor orientation and position on the human and can be critical to deriving criteria to distinguish walking patterns.

Figure 3.2: 6-axis IMU sensor (MPU6050)

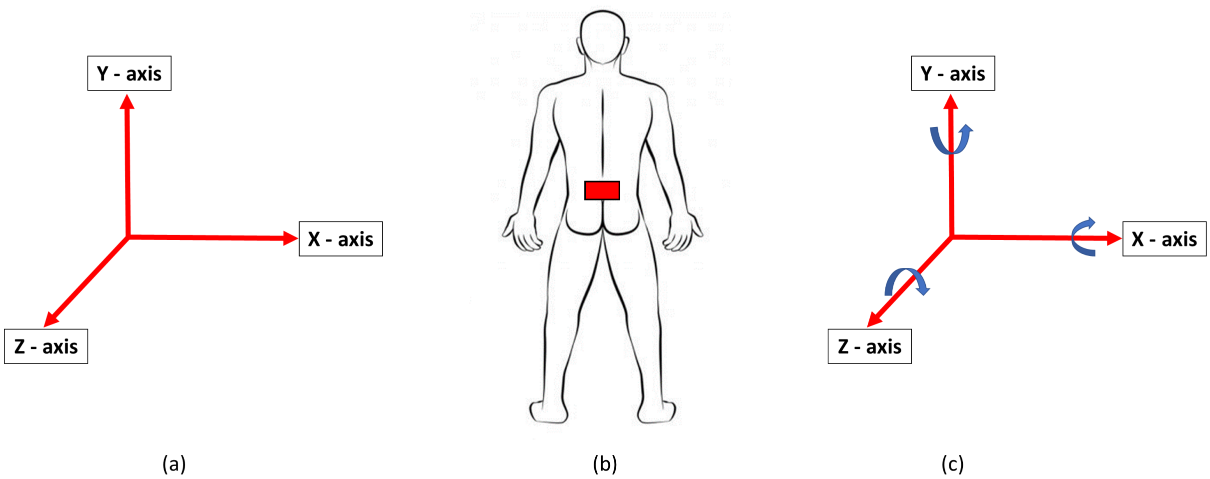


Figure 3.3: (a) Accelerometer orientation, (b) Sensor position - Lower back and (c) Gyroscope orientation

A device is constructed using Arduino Uno, IMU sensor, button, and a led (neo pixel) to record the walking pattern when it is positioned on the lower back. The schematic diagram for this setup is shown in Fig: 3.4. A waist pouch with adjustable bands (Fig: 3.5) holds the constructed device and the IMU sensor on the lower back. The data recorded by the sensor are collected in real-time by using Ardunio and Processing software running on a laptop.

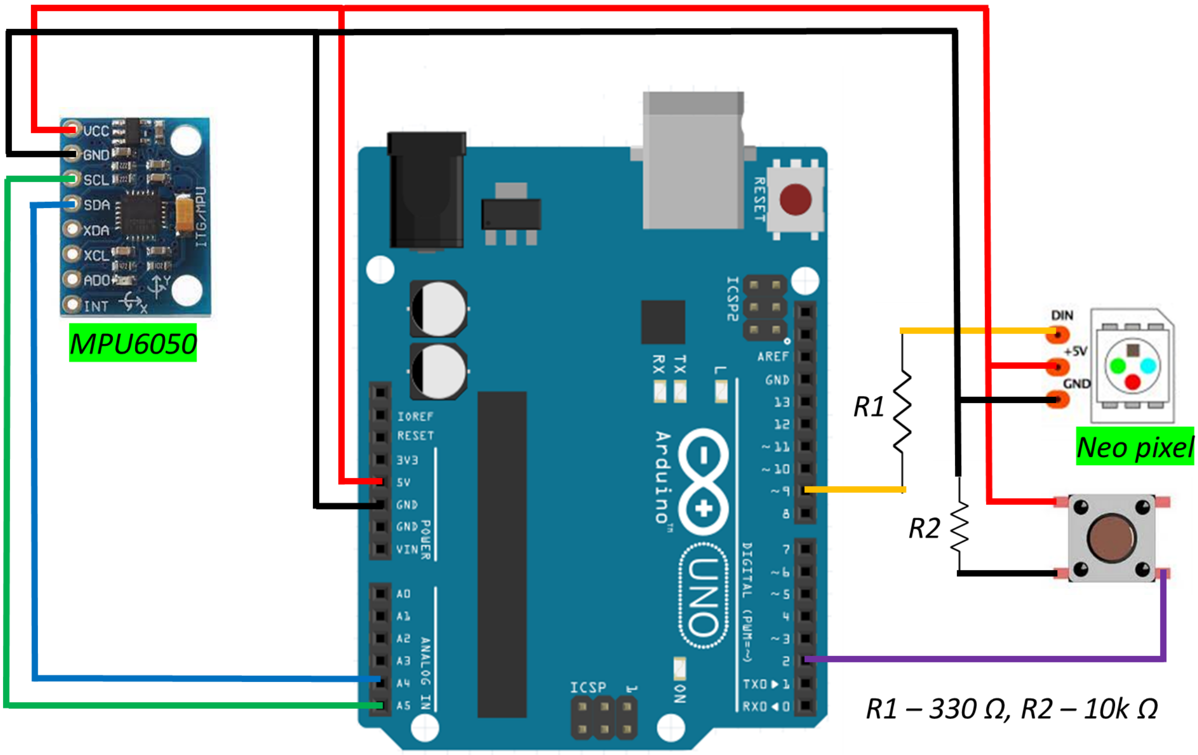


Figure 3.4: First development - Schematic diagram

Figure 3.5: First development - Pouch

The walking patterns were recorded with the help of the constructed device by instructing the user to press the button during the left foot heel-strike event. This was introduced to discover the values measured by the IMU during the heel-strike event. Fig: 3.6 presents the obtained results (left side-accelerometer, right side-gyroscope) of a user without prosthesis walking activity. The red dots in the image indicate the button pressed by the user for the left foot heel-strike event. The number of red dots present at alternating peaks differs because of the button pressed duration by the user for the left foot heel-strike event. The red dotted box in the figure showcases the repeating patterns observed in the measured signals for the walking activity. These patterns align with the [82][55] author's work where they used an IMU and lower back location to analyze parameters in walking activity.

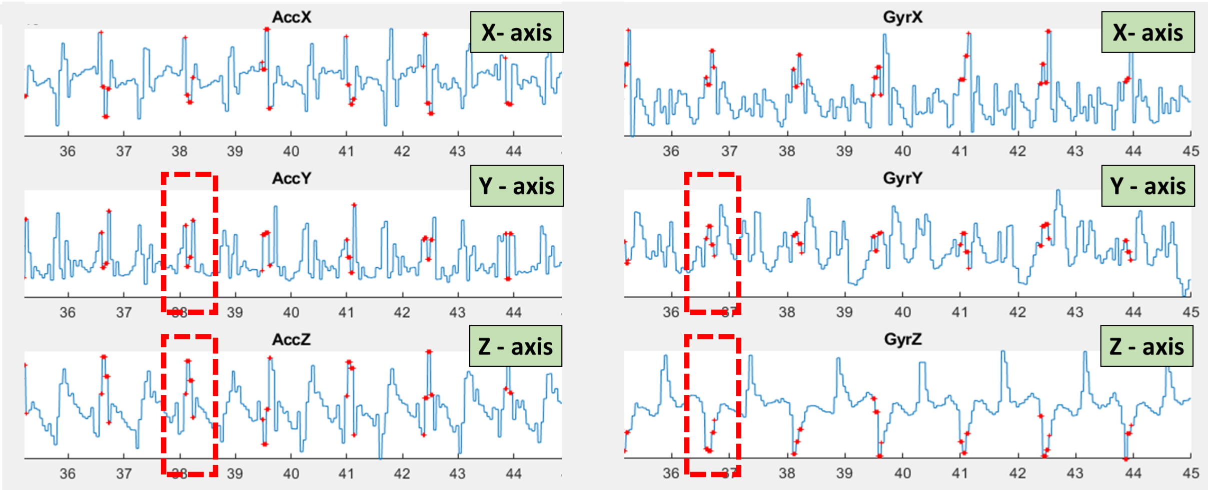


Figure 3.6: First Development - Walking patterns of a user without prosthesis

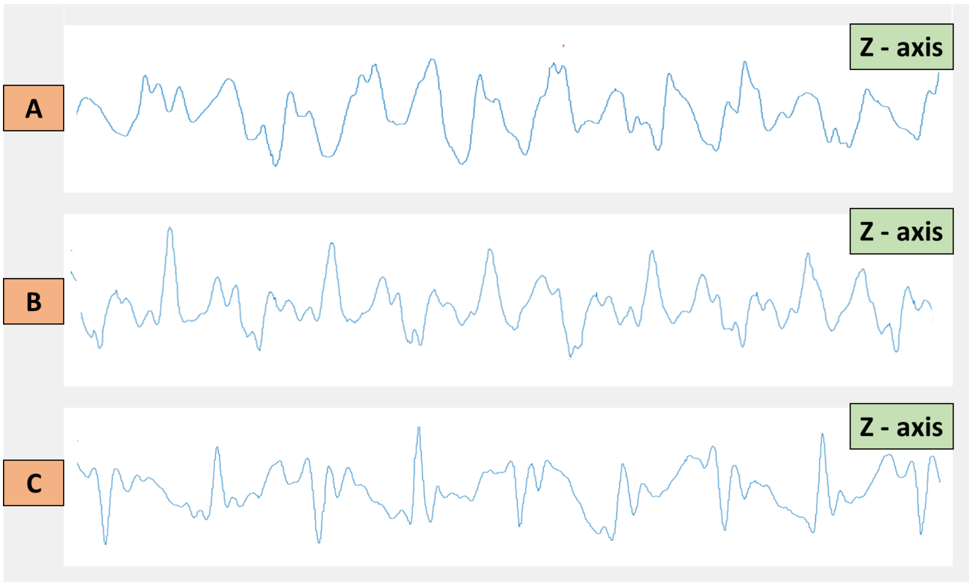


Figure 3.7: Different walking patterns generated for users without prosthesis along gyroscope Z-axis

Now, the peaks generated (red dotted box in Fig: 3.6) during the heel-strike event looked promising to develop a real-time algorithm for step duration, especially the angular velocity generated along Z-axis. However, when multiple users (Candidates A, B, C as shown in Fig: 3.7, 3.8) without prosthesis walking patterns are recorded to understand the peaks generated during heel-strike event, the angular velocity along Z-axis showcased different patterns and peaks for each candidate (Fig: 3.7). This observation leads to the conclusion that developing a real-time algorithm based on the peaks generated by the gyroscope can be complex. On the other hand, the accelerometer values measured along the Y-axis and Z-axis showcased consistent patterns (red dotted box in Fig: 3.8). These measurement values from the accelerometer could be used for the development of a real-time algorithm. The Straight Forward Data Analysis method focuses on this observation to determine the intermediate step duration for the walking activity. The implementation of this method is explained in detail in Chapter 5.

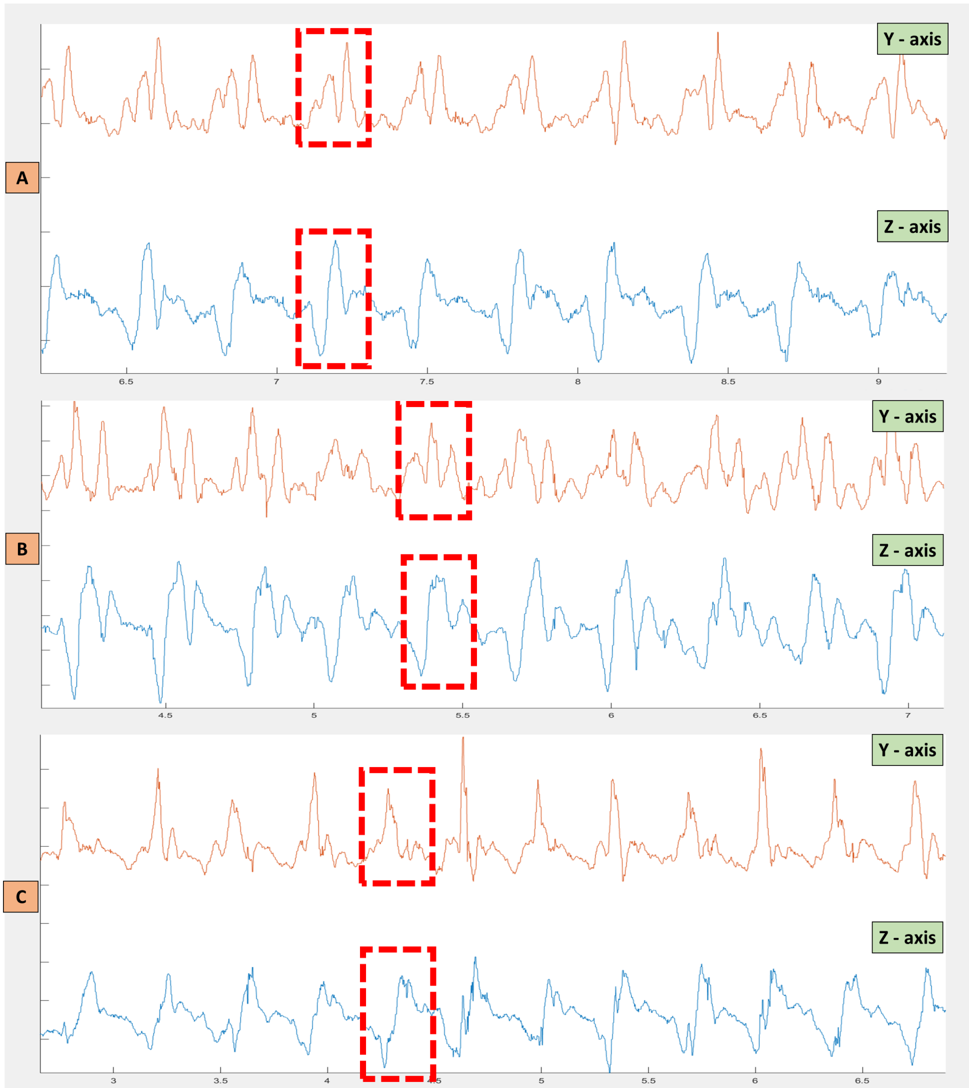
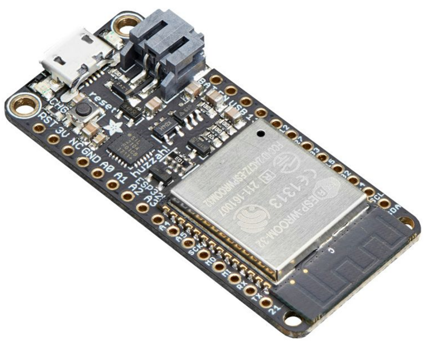


Figure 3.8: Similar walking patterns generated for users without prosthesis along accelerometer Y-axis and Z-axis

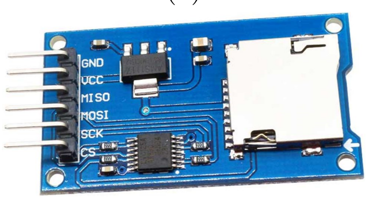
3.2 Second Development

The device described in section 3.1 represents a prototype to understand the IMU measurements for the lower back location and walking patterns of users without prosthesis. In the next step, using the prototype to collect few sample walking data, the device is upgraded to a more appropriate version. The design choices made for this version are more aligned with the design of a good wearable device. This upgraded device uses the same IMU sensor, button, and LED (neo pixel) used in the earlier prototype. However, for this new prototype, ADAFRUIT HUZZAH32 – ESP32 Feather Board (Fig: 3.9(a)) is picked for its more compact size, lightweight, and better specifications suitable for deploying a real-time algorithm. Moreover, in the earlier prototype, the real-time data are collected using a wired connection to a laptop, but in this version, a TF card reader module (Fig: 3.9(b)) is used to store data in a micro SD card. This SD card stores the data in real-time and can be accessed once the user is done with recording data. Plus, the usage of button functionality is changed in this version. The button is presently operated as a switch to turn on/off the data recording into the SD card. Even the LED light is combined with the button operation to provide the user feedback about the data recording operation. Moreover, the haptic motor (feedback) is unimplemented in this version because the criteria for determining the type of walking are not finalized yet. However, the addition of a haptic motor or relevant feedback choice will be considered in the final design/versions of the wearable device. In addition, the device designed in this section will represent the baseline for the following designs to come.

The following parameters are considered as default for the IMU measurements produced for the remainder of the report. The linear accelerations are measured for the $-8g$ to $+8g$ range, angular velocities are measured for $-500°/s$ to $+500°/s$ range, and the data collection is done at a 52Hz frequency. If any other parameters or devices are used for measurement, they will be mentioned explicitly for the relevant parts of the report.



(a)



(b)

Figure 3.9: (a) ESP32 feather board and (b) TF card reader module

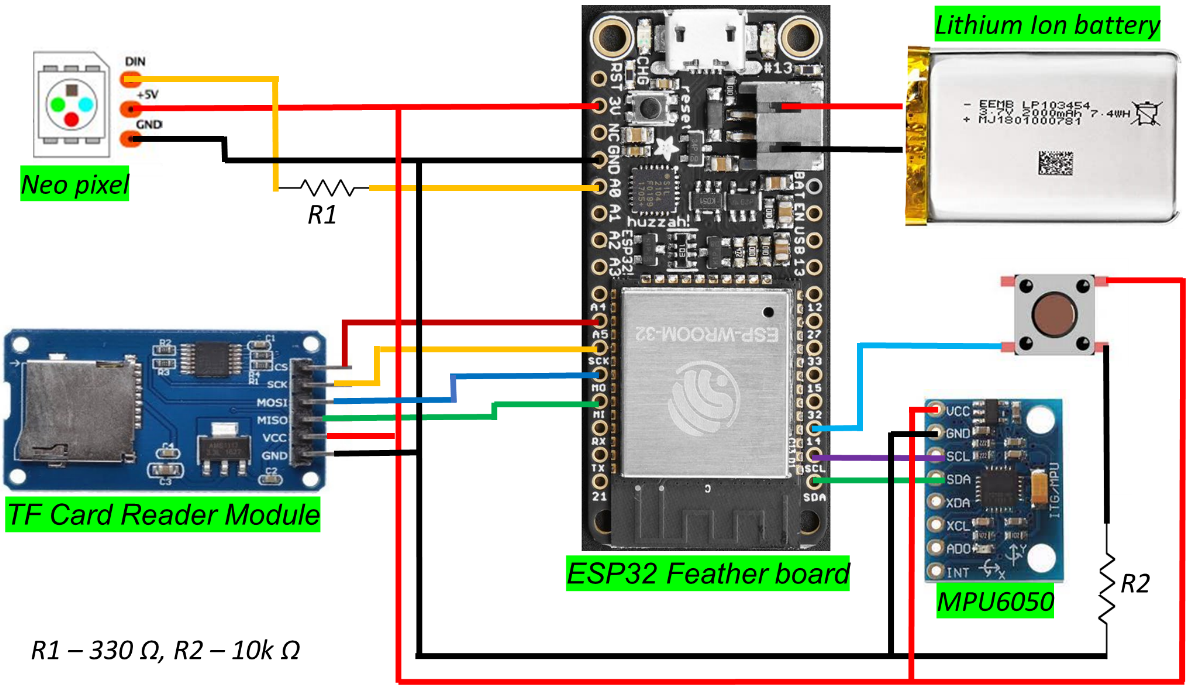


Figure 3.10: Second Development - Schematic diagram

(a) Outside

(b) Inside

Figure 3.11: Waist belt

The schematic diagram for the device constructed in this second development is referred to in Fig: 3.10. Plus, a new waist belt (Fig: 3.11) is designed with a soft fabric material that holds all the necessary hardware required for the data collection process and adjustable bands, ensuring the user's choice of comfort. The material used for this belt design is expected not to cause any discomfort while performing the walking activity. As seen in the image (Fig: 3.11(a)), the device will be held inside the pocket designed on the belt.

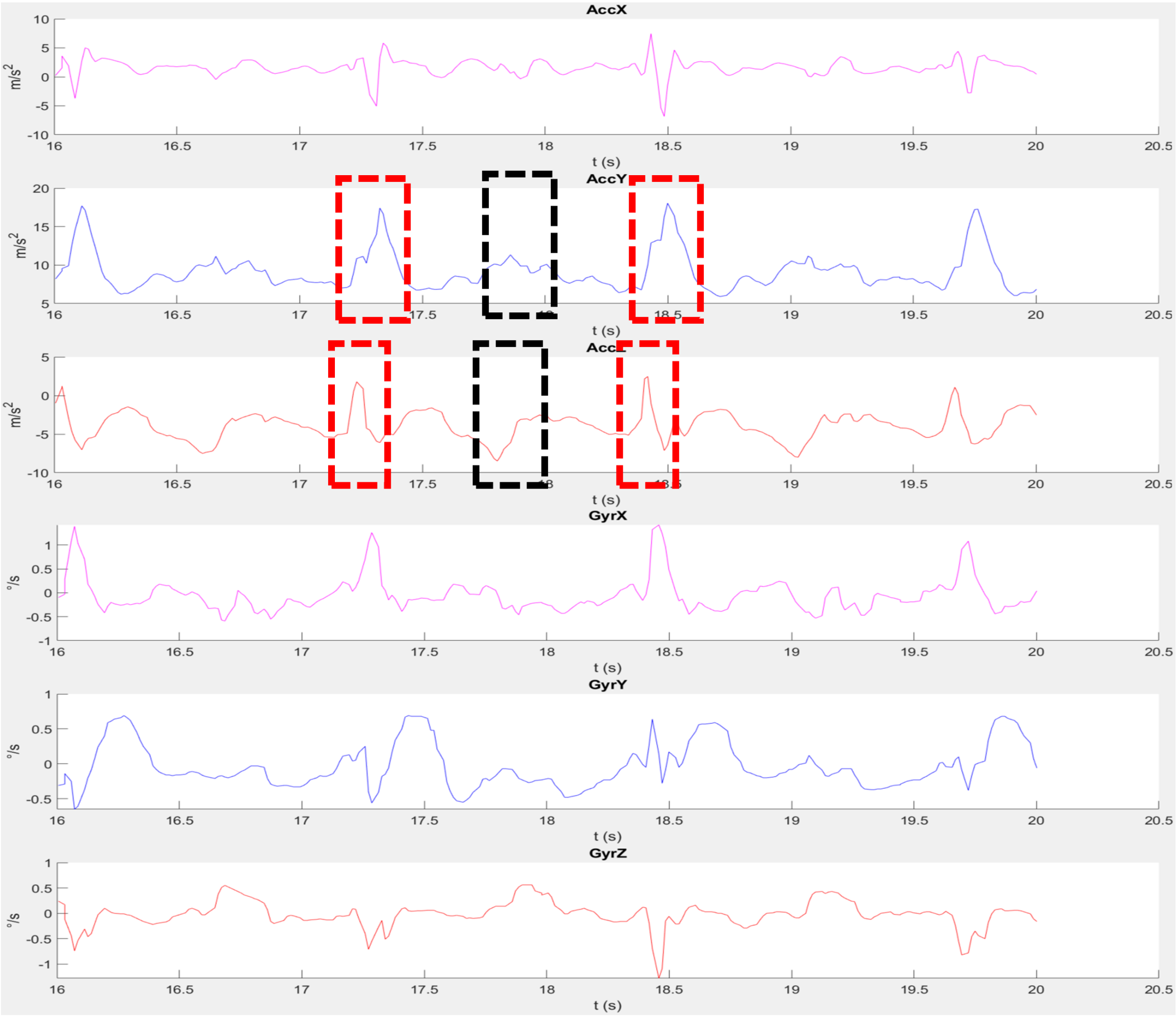


Figure 3.12: Walking patterns recorded for candidate A with prosthesis in right knee

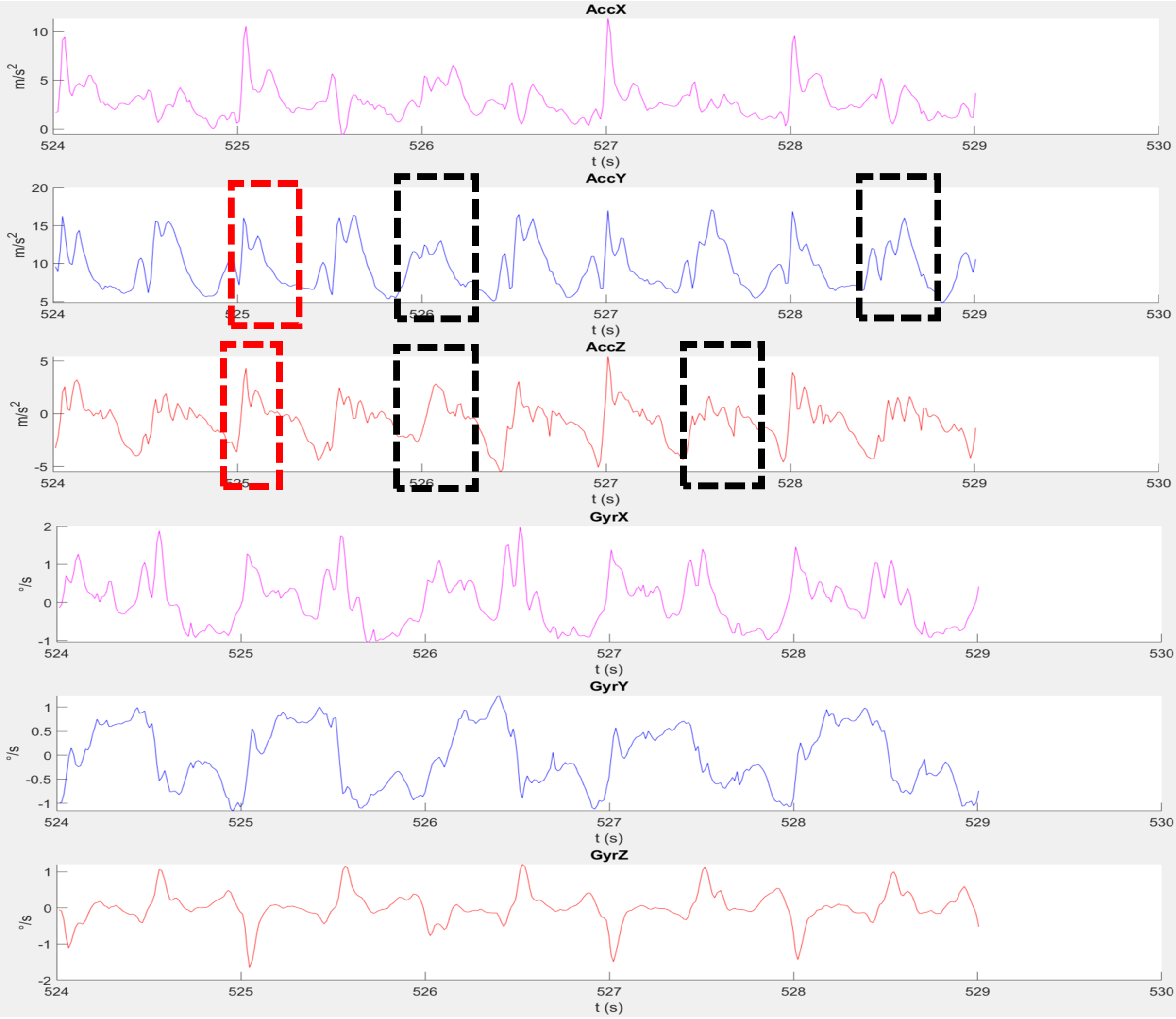


Figure 3.13: Walking patterns recorded for candidate B with prosthesis in left hip

By using the latest device, the walking patterns for the users with the prosthesis are collected for two candidates (candidate A, B). Fig: 3.12, 3.13 presents the recorded data for these candidates. The peaks/patterns generated during the heel-strike event showcased similar patterns (red dotted box in Fig: 3.12, 3.13) observed in users without prosthesis walking. However, this pattern/peak is visible (red dotted box in Fig: 3.12, 3.13) for the non-operated leg or side of the hip but not clearly distinguishable (black dotted box in Fig: 3.12, 3.13) for the prosthesis leg/hip. In addition, the patterns generated are not always constant for the same leg, which indicates the user is not maintaining consistent walking. Overall, these observations present that the patterns/peaks generated by the accelerometer along Y-axis and Z-axis showcases similar behavior for the users with or without prosthesis walking. But there was more inconsistency in the peaks generated for the users with prosthesis walking (black dotted box in Fig: 3.12, 3.13). The term inconsistency addresses the sharpness of the peaks generated during the heel-strike event.

The inconsistency in peaks presents a complexity in understanding the right peaks generated at the heel-strike event. In addition, it could be difficult for the real-time algorithm (straight forward data analysis method) to identify the exact peak caused by the heel-striking event. The literature from chapter 2 presented methods to detect the heel-strike by performing offline analysis/post-processing. However, implementing these methods cannot be rewarding because they were developed for offline processing, which is not the approach aimed in this thesis (real-time). Therefore, an alternative approach to detect the accurate heel-strike event can be performed by adding a pressure sensor (located at the heel) inside the user's shoes. By executing this, the heel-strike event can be determined in real-time smoothly even when there are inconsistencies in the peaks generated. Moreover, a deeper understanding of the consistent and inconsistent peaks at heel-strike events could be obtained for the users with and without prostheses. As well the accuracy of the real-time algorithm can be verified with the help of the pressure sensors. However, this addition of a pressure sensor is not an ideal design choice for a wearable device. But this can be temporarily added for gathering more information during the heel-strike event by the users with and without prostheses.

After looking at the observations from the first and second development, a deeper study needs to be performed to understand the users with and without prosthesis walking patterns to derive criteria to distinguish the type of walking. Moreover, the study needs to focus on intermediate step duration, which is necessary to verify the hypothesis. The addition of a pressure sensor to validate the real-time algorithm can additionally be used to determine the step duration and intermediate step duration for the walking activity[1]. After completing the verification of the hypothesis and validation of the real-time algorithm, the pressure sensors can be removed from the device. In conclusion, the temporary addition of pressure sensors to the wearable device and deeper study (procedure and results) are explained in the following chapter.

[1]The process of determining step duration and intermediate step duration with the help of pressure sensor is explained in the next chapter

Chapter 4

Study

This chapter focuses on explaining the deeper study performed in understanding the walking patterns, verifying the hypothesis, and determining criteria to distinguish the type of walking. This study is conducted on participants with and without hip/knee prostheses. Moreover, the temporary addition of pressure sensors to the constructed device in the previous chapter is explained in this chapter. The usage of the pressure sensor to determine the intermediate step duration is done in this chapter. Finally, the results obtained from the study are presented in their respective sections.

4.1 Temporary Addition Of Pressure Sensors

Velostat pressure sensors are used in this study. This type of pressure sensor is preferred due to its lightweight, flexible polymer-based material, which allows developing a sensor of the desired shape. Along with proper housing, it does not constrain/distract the subjects [19]. With this pressure sensor, the heel-strike event of the subjects can be recorded accurately. The pressure sensors are designed as shown in Fig: 4.1. These pressure sensors are constructed[1] not to cause any discomfort to the participants, are easy to wear, and precisely detect heel-strike events. These pressure sensors are added to the device constructed for the analysis performed in the second development stage. The schematic diagram for the updated device is shown in Fig: 4.2. The usage of device functionality to record the data remains the same, as discussed in the previous chapter. More detailed use of the button and LED light indication for the data collection process is explained in Appendix: A.

[1]https://cdn-shop.adafruit.com/datasheets/HandcraftingSensors.pdf
https://www.adafruit.com/product/1361

Figure 4.1: Designed pressure sensor

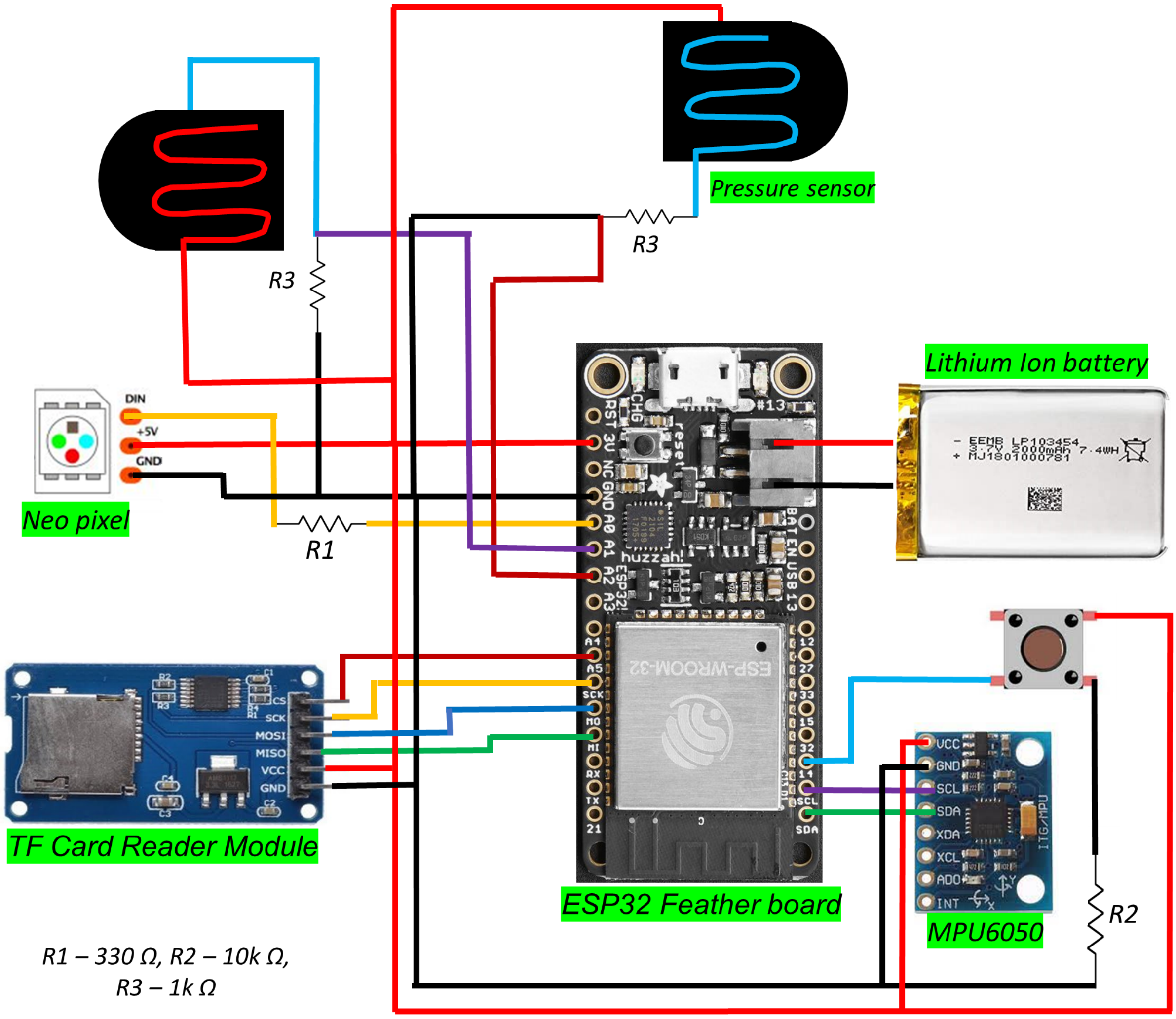
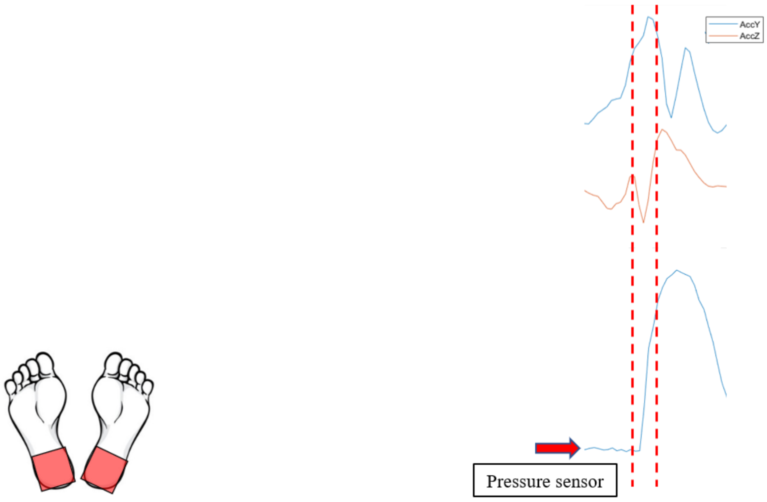


Figure 4.2: Schematic diagram - pressure sensors



(a) Pressure sensor position (b) Identification of heel-strike

Figure 4.3: Usage of pressure sensor

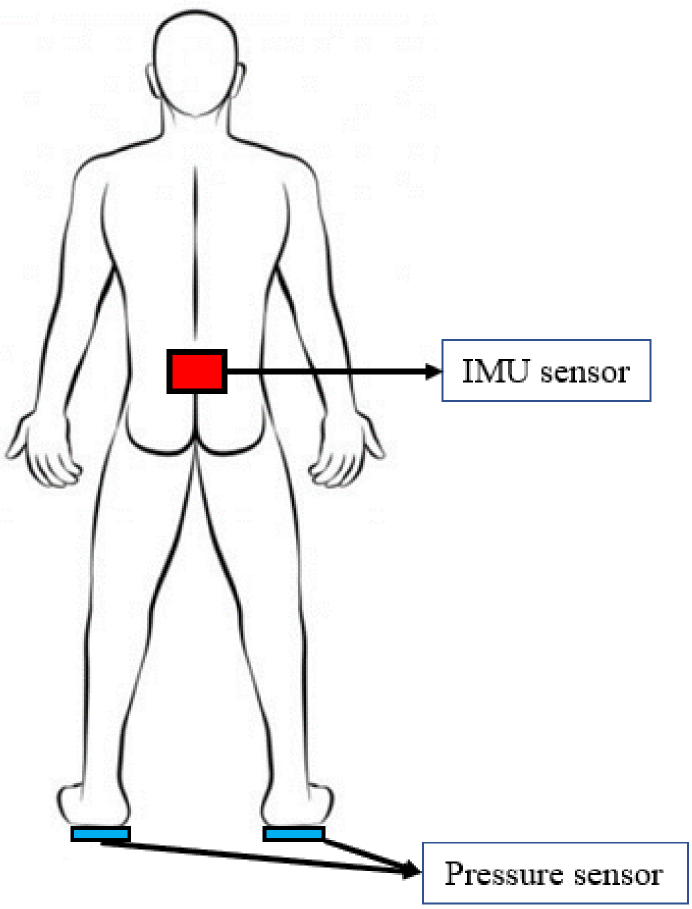


Figure 4.4: IMU sensor & Pressure sensor location

Fig: 4.3(b) presents the accelerations recorded during the heel-strike event. This is achieved by using a velostat pressure sensor on the bottom of the feet, as shown in Fig: 4.3(a). Besides, for the study performed in this chapter, Fig: 4.4 illustrates the sensors' location on the body. Because of the pressure sensor positioned at the bottom of the heel, the sensor[2] records the pressure when the heel strikes the ground during the walking activity. Thus, providing the instance/window to determine the step duration and intermediate step duration. By using the signals generated from the pressure sensors as shown in Fig: 4.5, the calculation of the left step duration, right step duration, intermediate step duration between right and left foot ($\boldsymbol{RL}$), and intermediate step duration between the left and right foot ($\boldsymbol{LR}$) is performed. This calculation will help in verifying the hypothesis as well helpful in validating the real-time algorithm.

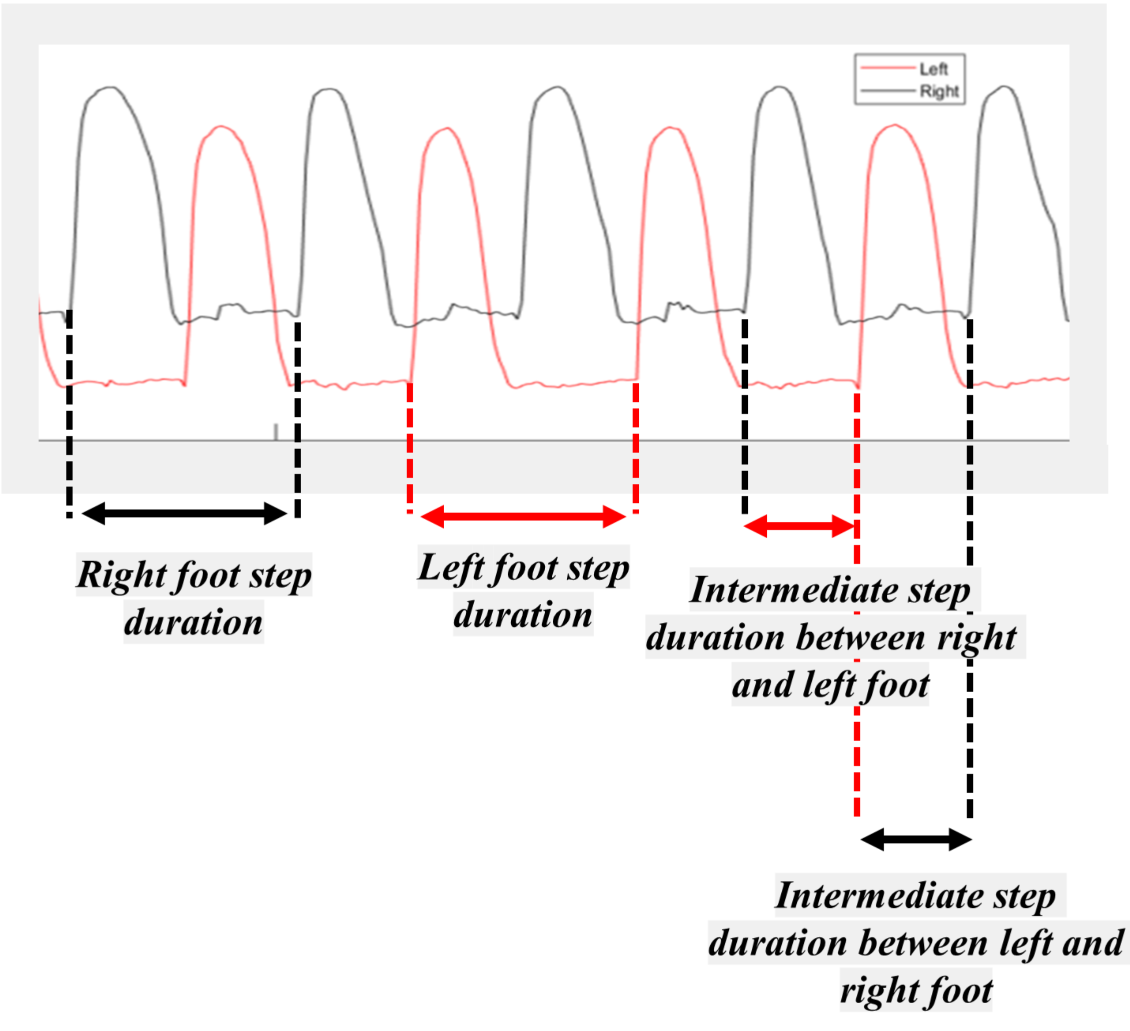


Figure 4.5: Calculation of intermediate step duration and step duration

[2]The value of pressure generated (amplitude) is unconsidered in this report because the focus is on identifying the instance of a heel-strike event but not the amount of force used by the user.

4.2 Data Collection/Study Procedure

Participants are requested to participate in this research study voluntarily after the screening process. This screening process applies to participants with prostheses. The following are the screening criteria:

- Must have undergone hip/knee surgery in recent years/months($<= 1 year$)
- Must be vaccinated completely (COVID 19), for the safety of the participants and the researcher. (We do not expect that excluding the non-vaccinated citizens will make a change in the set of walking data)

The data collection for participants with a prosthesis will be done at the physiotherapeutic center, before or after a physiotherapy session planned for their recovery trajectory, in collaboration with the chief physiotherapist of the center [31]. Also, few participants visited the physiotherapeutic center exclusively for the study purpose. The users will receive the forms beforehand by email; they also will receive them in a paper version at the physiotherapeutic center and can decide to participate in this experiment or not. If the user decides to withdraw after participating in the experiment, the data for the user will be permanently deleted from the database and strictly not considered in the study. Whereas for the participants without prostheses, the data collection is conducted inside the university. The data will be safely stored and processed according to AVG guidelines. In addition, the data are handled discreetly; anonymity of participants' data is guaranteed and will never be disclosed to third parties.

The criteria for performing this study outside the university are met, and approval from the university's ethics committee is taken. The brochure and consent forms for the experiment are provided in *Appendix B*. The experiment focuses on obtaining data from the participants' walking patterns. The task for the participants is to walk in a straight path for 25s to 35s by wearing the measurement device on the lower back for each run. The device will record *(52Hz)* the accelerations and heel-strike events generated when participants are walking.

The data collection is taken four times for all the participants. This helps in obtaining more data to analyze the diverse walking patterns. Moreover, the subjects with a prosthesis can be biased to walk better than their normal walking due to the experiment setup/environment. This behavior is noticed from the participated candidates in the sample data collection in the previous chapter (section: 3.2). This can lead to a data set that might not capture the precise walking pattern of the subjects with prostheses. To overcome the bias, the participants were distracted for two runs during data collection. The purpose of this distraction is to ensure the participants are not focused on how they are walking. The distraction to participants is achieved by continuously involving the patients in a conversation. By performing this, we hope that the natural walking style for the participants during the walking activity can be captured. However, this need for distraction during walking represents a hypothesis and needs more studies to confirm.

4.3 Study Results - Participants Without Prosthesis

The experiment is completed as mentioned in the before sections on seven subjects without a prosthesis. Fig: 4.6, 4.7 illustrates the sensor measurements recorded during walking activity. These measurements among the subjects without prostheses registered various patterns (red dotted box in Fig: 4.6, 4.7). The most recurrent visible pattern is observed for accelerometer readings along the *Z-axis* (black dotted box in Fig: 4.6, 4.7). This pattern exactly fits with the other author's research [82][55]. This pattern represents the accelerations generated when the heel-strike event during walking activity. These results are possible because of the location of the IMU sensor, i.e., lower back.

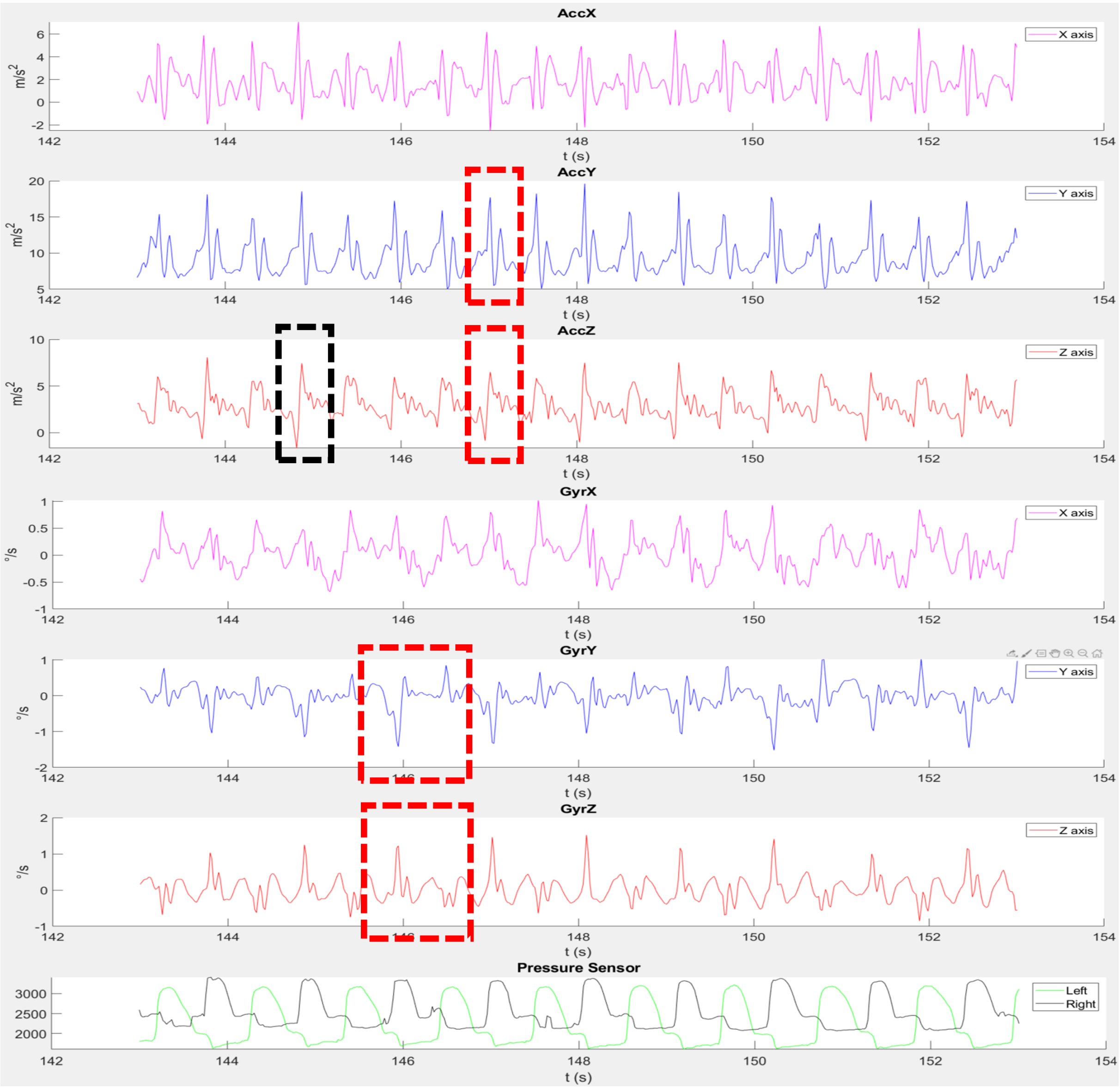


Figure 4.6: Walking pattern without prosthesis - candidate 2

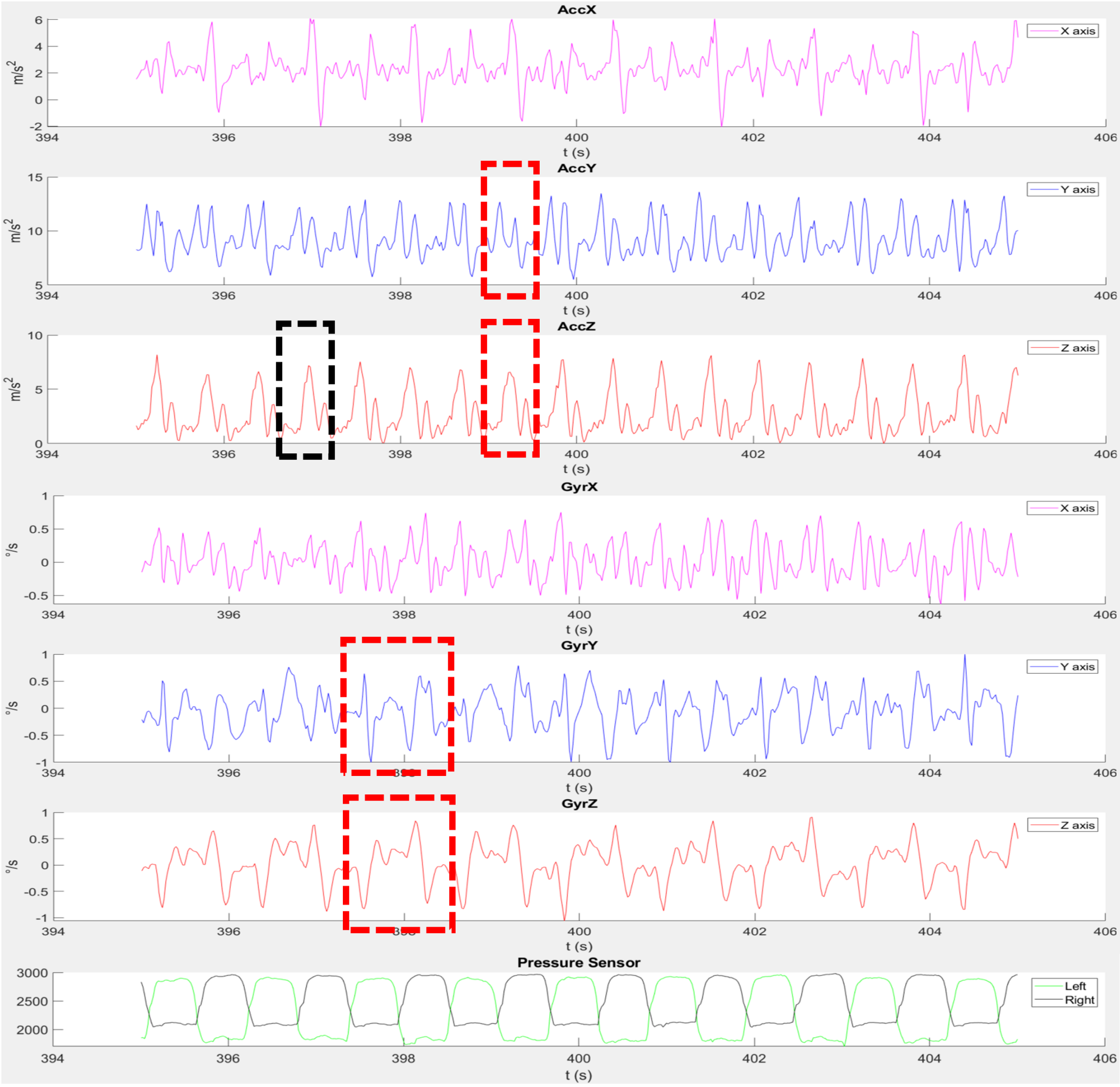


Figure 4.7: Walking pattern without prosthesis - candidate 3

During heel-strike events, the accelerometer records upward acceleration caused along the *Y-axis* and forward/backward acceleration caused along *the Z-axis.* The gyroscope measures the angular velocity caused by the pelvis movement along the *Z-axis* and the *Y-axis* which is caused by the hips motion during walking. Fig: 4.8(a) illustrates the cardinal planes overlapped with the sensor axes used for this report to understand the movement of the pelvis during walking activity. Fig: 4.8(b),(c),(d) displays the pelvis movement along its cardinal planes. Also, these images present the terminology about the movement associated to the pelvis w.r.t each cardinal plane and act as a guide for the analysis of this chapter.

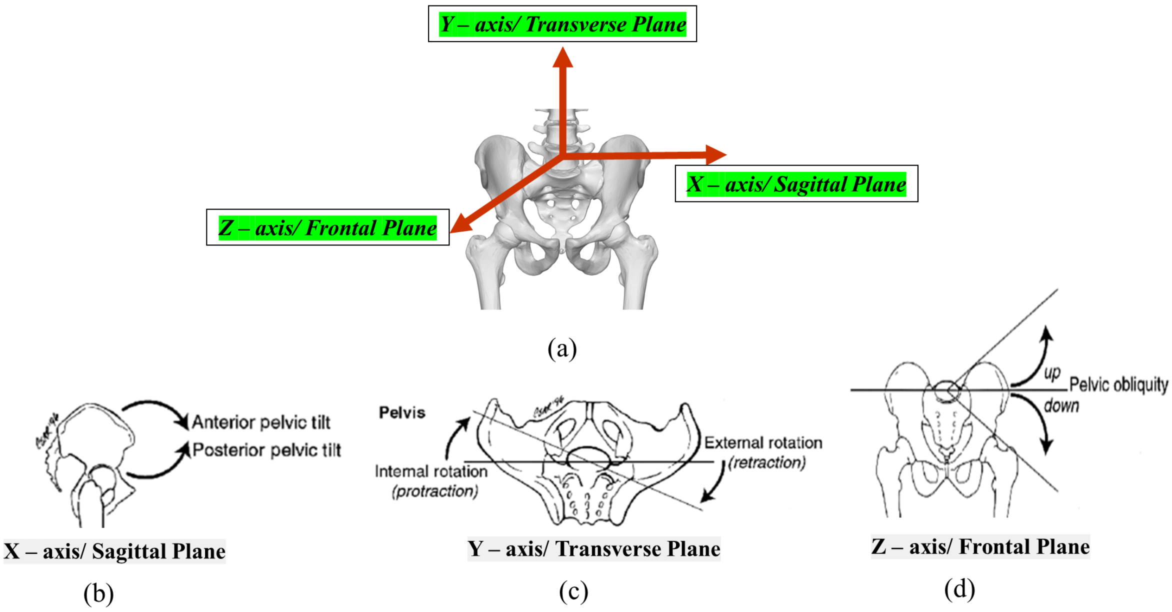


Figure 4.8: Overlapping of IMU sensor axis with cardinal axis

Fig: 4.9, 4.10, 4.11 presents linear accelerations and angular velocities caused for all the participants[3] without prosthesis. Fig: 4.9 correlates the acceleration and velocities caused during the heel-strike event in the left and right foot for all the participants. This figure presents how the same person's accelerations and angular velocity values differ during right and left foot heel-strike events. Whereas, Fig: 4.10, 4.11 contrasts the accelerations and velocities measured for the participants left and right foot heel-strike events. These figures display all the participants accelerations and angular velocity values generated for the left foot and right foot, respectively. It also illustrates how each walking style matches/differs with the rest of the participants w.r.t left/right foot.

[3]Mean and standard deviation (black vertical line) calculated for 20 consecutive steps

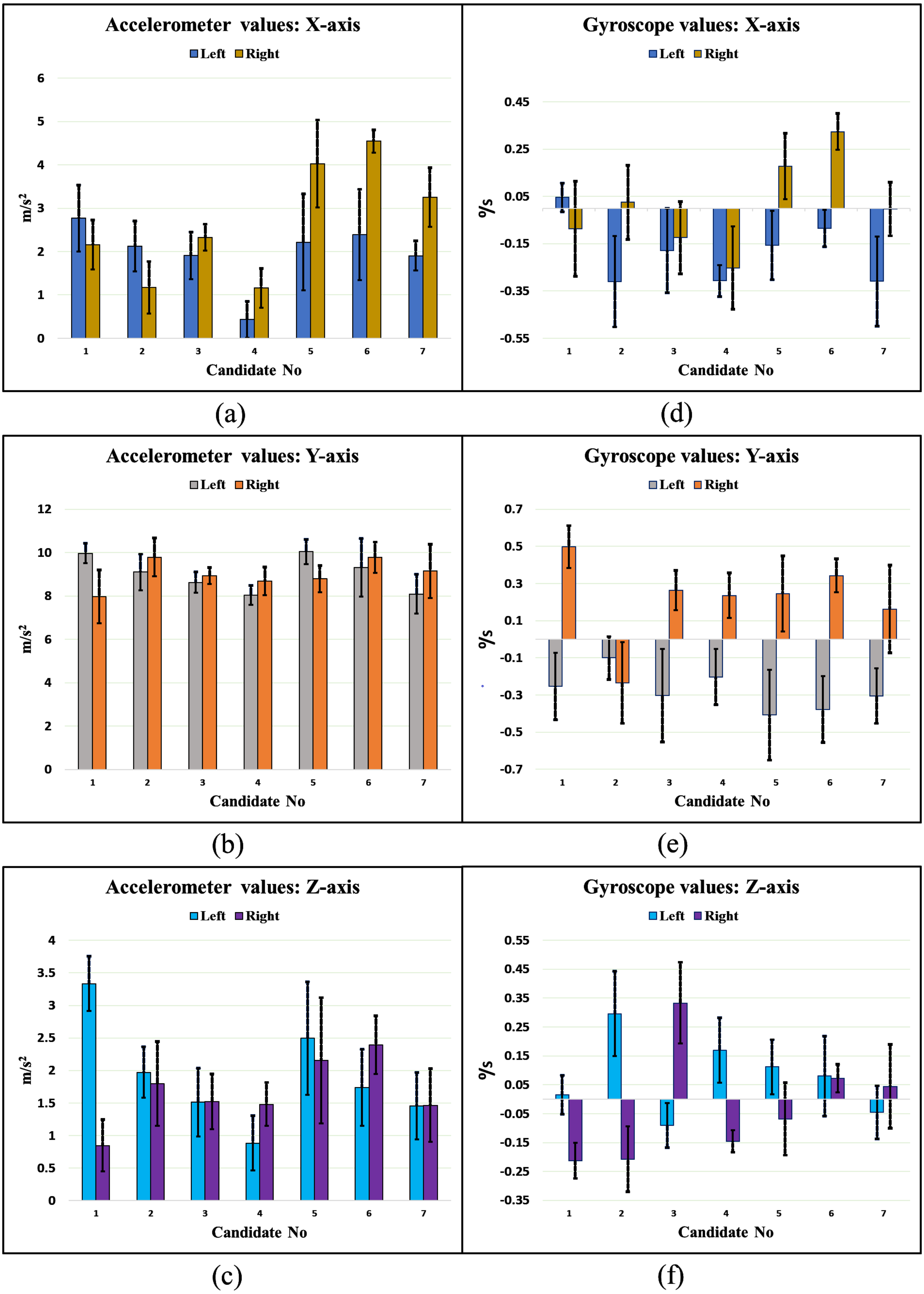


Figure 4.9: Without prosthesis - Accelerations measured during left and right foot heel-strike event

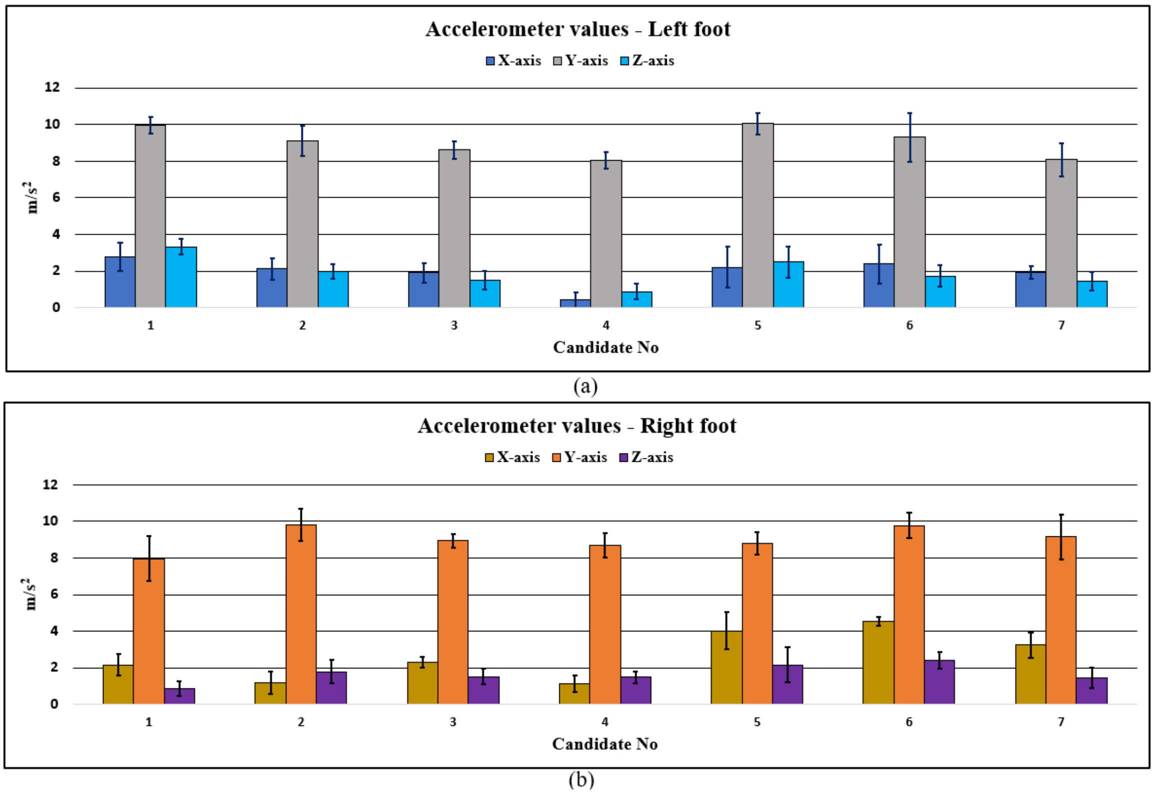


Figure 4.10: Without prosthesis - Linear accelerations measured during (a) left foot heel-strike event (b) right foot heel-strike event

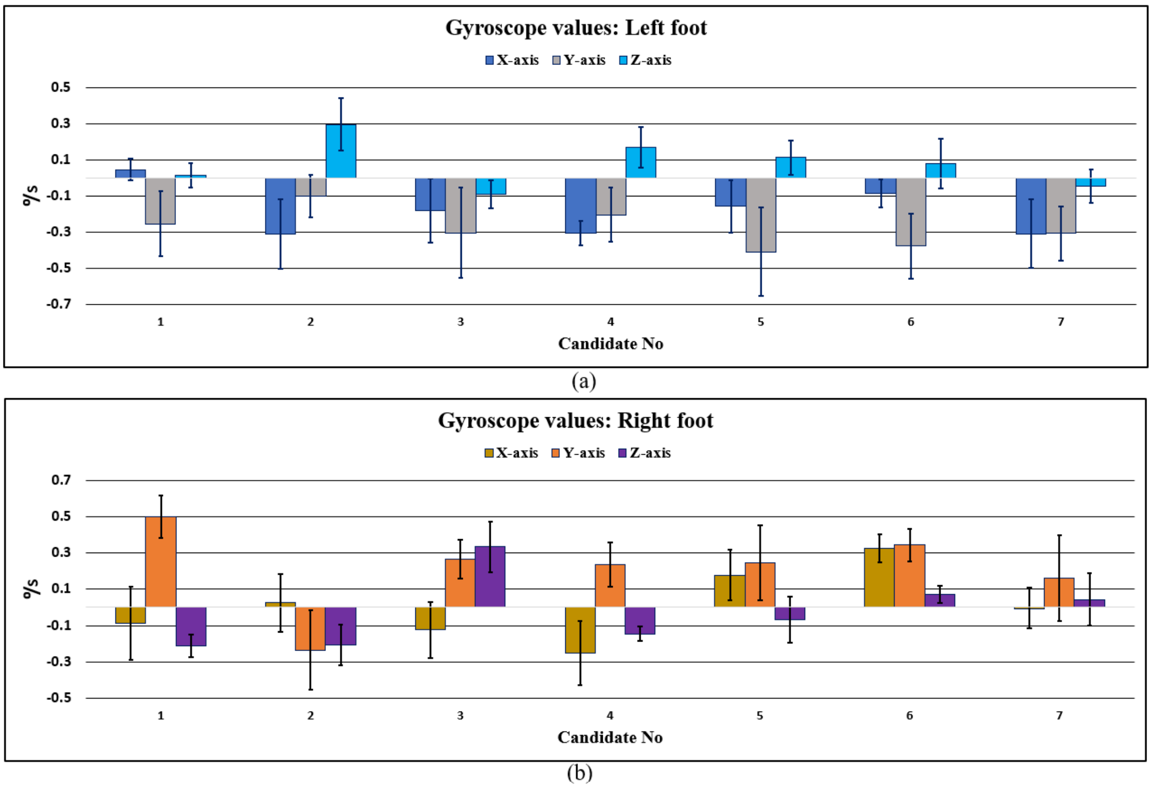
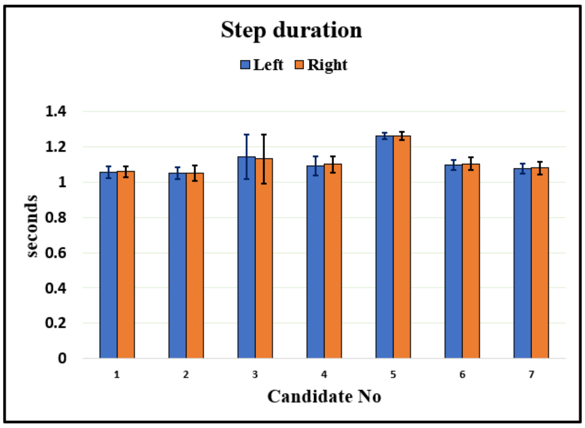


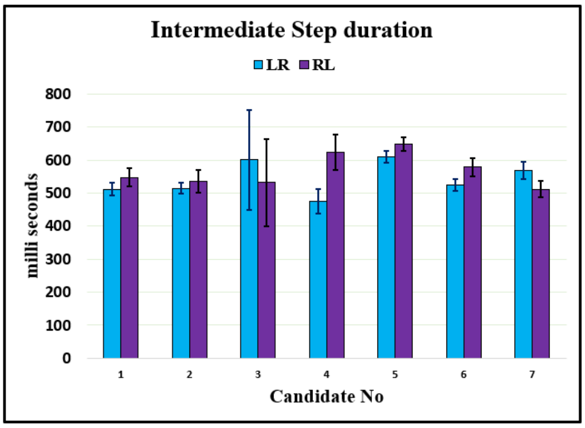
Figure 4.11: Without prosthesis - Angular accelerations measured during (a) left foot heel-strike event (b) right foot heel-strike event

The values from the figures explain the acceleration and velocity values will primarily differ for left and right foot for the same participant. Also, these measured values differ for each participant. The accelerations measured for right and left foot along Y-axis are in the range of $8m/s^2$ to $10m/s^2$ (Fig: 4.10) whereas the other two axes recorded in between $1m/s^2$ to $3m/s^2$. This observation indicates that the participants have similar values during the transition from the stance phase to the swing phase. Moreover, it also illustrates some individuals can have (candidates 1,4,5,6 in Fig: 4.9(a),(b),(c)) linear acceleration of one foot higher than the other foot along *X, Y, Z-axis*,i.e., the heel contacts the ground at different speeds for each leg. Equally, the pelvis movement (measured by gyroscope along *Z-axis* and *Y-axis*) indicates some individuals (candidates 1,2,3 in Fig: 4.9(e),(f)) rotate a lot during walking activity.

The measurements in Fig: 4.9(e),(f) indicate that the pelvis rotation along *Y-axis* and *Z-axis* are opposite for the right and left foot,i.e., each side of the pelvis rotates clockwise (up the pelvic obliquity, Fig: 4.8(d)) along Z-axis and anti-clockwise (external rotation, Fig: 4.8(c)) along Y-axis and vice versa. This behavior is observed due to the left and right hip concurrent movement during the walking stance and swing phase. Also, some participants (candidates 1,2,3 in Fig: 4.9(e),(f)) tend to maintain higher angular velocities in one direction than in the other direction,i.e., the pelvis rotates more for one foot at the heel-strike event than the other foot heel-strike event. There are candidates (candidate 2 in Fig: 4.9(e), candidate 6 in Fig: 4.9(f)) where they are exhibiting pelvis rotation in only one direction during the heel-strike event,i.e., the pelvis is rotated in the same direction for both foot heel-strike events. However, for the same candidates, the linear acceleration values looked similar to other participants data. The anterior and posterior pelvic tilt (Fig: 4.8(b)) indicates differing patterns (Fig: 4.9(d)) for each participant. Also, no strong correlation is seen with the other pelvic rotations along the Z-axis and Y-axis. Finally, the standard deviation marking (black vertical line) in Fig: 4.9, 4.10, 4.11 indicate the measured values are unconstant during walking, i.e., they differ for each heel-strike event.



(a)



(b)

Figure 4.12: Without prosthesis - (a) Step duration (b) Intermediate step duration

Now, looking deeper into these recorded measurements, the heel-strike events identified with the help of pressure sensors are used to calculate the step-duration and intermediate duration between right-left (RL) and left-right (LR) feet. Fig: 4.12(a) presents the step duration, and Fig: 4.12(b) presents the intermediate step duration measured for all the participants without prosthesis in the experiment[4]. This data showcases that step duration *(both legs)* for the majority of the participants is $\approx 1sec$ (Fig: 4.12) which is identical to the value mentioned by the author [75]. Furthermore, the intermediate step duration is relatively equal for right-left and left-right feet. However, candidate 3 and candidate 4 presented varying values compared with other candidates, as seen in Fig: 4.12(b) (candidate 3 - standard deviation marking for candidate 3 and candidate 4 - the larger difference in LR and RL). These results indicate probable asymmetric walking for the users without hip/knee prostheses. The likely reason for these measurements can be one leg is shorter/longer than the other leg. However, a deeper investigation on users without prostheses is required in identifying the cause for this behavior. Also, there are participants (Candidate 5 in Fig: 4.12(a)) whose step duration is $\approx 10\%$ *to* 20% higher than the usual. Similarly, these participants have higher intermediate step duration values (Fig: 4.12(b)). The probable reason for these measurements is that the participants have more extended legs/taller or walk slightly faster than others. Overall, the walking patterns, acceleration, and velocity measurements showcased diversity majorly for every candidate. At the same time, the step duration and intermediate step duration presented a consistent value for the participants.

[4]These calculations are performed manually for twenty-eight consecutive steps from the collected data.

4.4 Study Results - Participants With Prosthesis

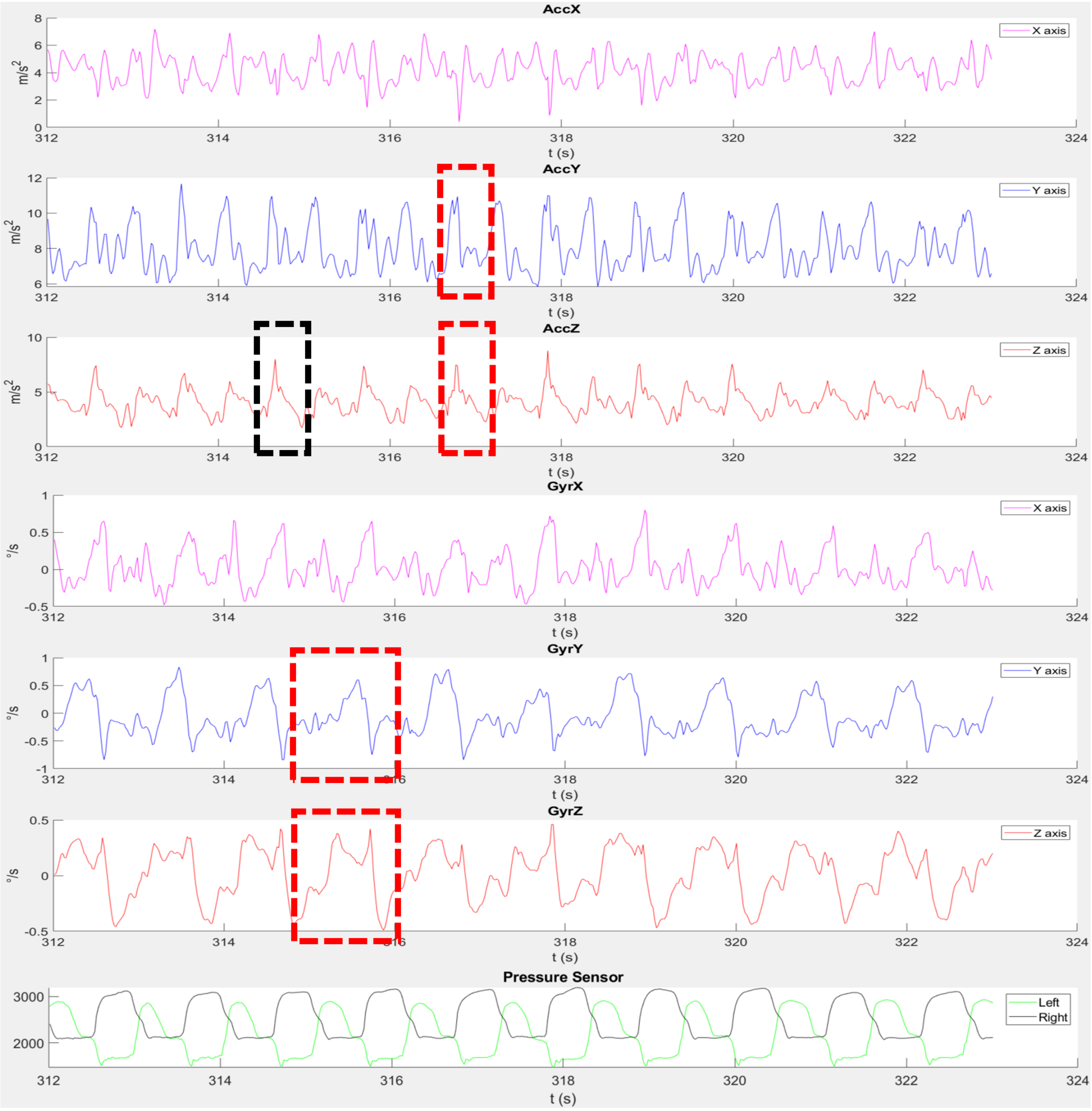


Figure 4.13: Walking pattern with prosthesis- candidate 1 (left hip)

The experiment is completed as mentioned in the before sections on 11 subjects where six candidates have undergone right knee surgery and have a prosthesis. Five candidates have undergone hip surgery (three left, two right) and have a prosthesis. Fig: 4.13, 4.14 illustrates the sensor measurements recorded during walking activity for the subjects undergone hip surgery *(left hip)* and knee surgery *(right knee)*, respectively. The walking patterns generated for participants who had undergone hip surgery (red dotted box in Fig: 4.13) and knee surgery (red dotted box in Fig: 4.14) showcased different patterns. Also, no two participants undergone similar surgery did not present consistent/identical patterns during walking. However, the only significant general pattern observed was during a heel-strike event (black dotted box in Fig: 4.13, 4.14). It measured similar patterns (red dotted box in Fig: 4.13, 4.14) along *Z-axis* and almost similar patterns along *Y-axis*, showcasing that the heel-strike event for subjects with prosthesis resembles the heel-strike event of the participants without prosthesis. Additionally, the linear accelerations measured along these axes (*either Y-axis or Z-axis*) showcased different patterns where the alternating heel-strike events recorded lesser or higher values than before the heel-strike event. This behavior demonstrates a correlation between the operated lower limb *(undergone surgery)* and the un-operated lower limb of the participants. Because the subjects are trying to avoid intentionally/unintentionally the efforts/stress on the operated side of the lower limb, this observation is confirmed by comparing the activation of the pressure sensors on both legs during heel-strike events. This investigation agrees with the physiotherapist's explanation presented during the interview *(Section: 2.1.1)*.

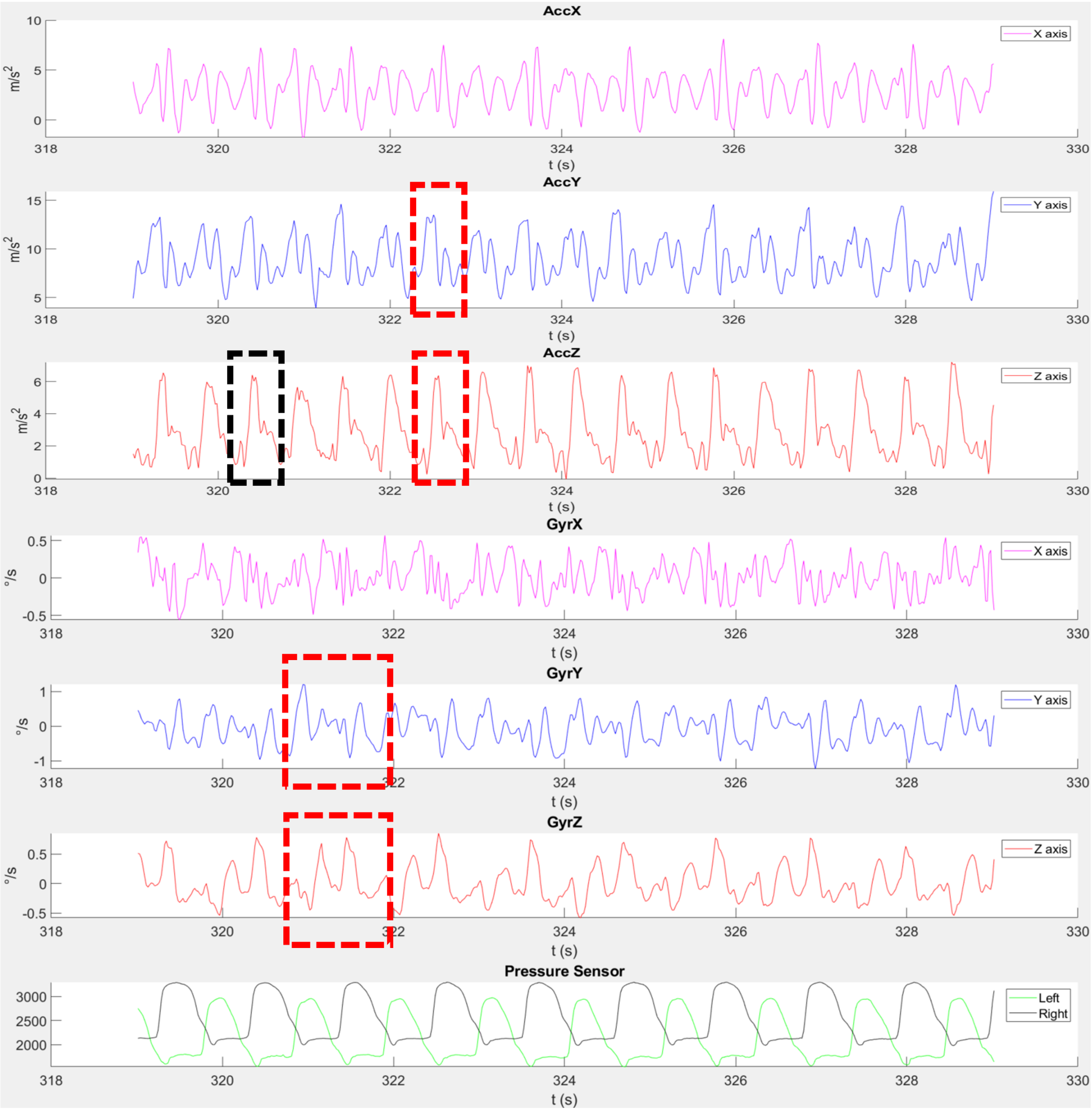


Figure 4.14: Walking pattern with prosthesis - candidate 2 (right knee)

The results for the participants with the hip and knee prosthesis are discussed in separate sections to understand walking patterns better and derive criteria to distinguish the type of walking. However, the hip and knee prosthesis's step duration and intermediate step duration are discussed at the end of this section to compare the results better.

4.4.1 Hip Prosthesis

Fig: 4.15, 4.16, 4.17 presents the measurements recorded for linear accelerations and angular velocities for all the participants[5] with hip prosthesis. The red stars on the figures indicate the side (left or right) of the prosthesis present for that participant's hip. Fig: 4.15 correlates the accelerations and velocities caused during the heel-strike event in the left and right foot for all the participants. This figure presents how the same person's accelerations and angular velocity values differ during right and left foot heel-strike events. Whereas, Fig: 4.16, 4.17 contrasts the accelerations and velocities measured for the participant's left and right foot heel-strike event. These figures display all the participants accelerations and angular velocity values generated for the left foot and right foot, respectively. It also illustrates how each walking style matches/differs with the rest of the participants w.r.t left/right foot.

The values from the figures explain the acceleration and velocity values will primarily differ for left and right foot for the same participant especially for the accelerometer values along X-axis (Fig: 4.15(a)). Also, these accelerations values and velocities differ for each participant. The accelerations measured for right and left foot along Y-axis are in the range of 7.5m/s^2 to 11m/s^2 (Fig: 4.16) whereas the other two axes recorded in between -0.5m/s^2 to 4m/s^2 . Moreover, it also illustrates some individuals can have (candidates 3, 4) in Fig: 4.15(b)) linear accelerations higher than the remaining participants during both foot heel-strike events (Fig: 4.16). Also, for the same candidates, the accelerations along the Z-axis (Fig: 4.15(c)) are very small when compared with the other participants during the heel-strike event.

The pelvis movement (measured by gyroscope along *Z-axis* and *Y-axis*) indicate some individuals (candidates 2,3, in Fig: 4.15(e),(f)) pelvis rotation is very high in one direction during walking activity. Plus, the angular velocities (pelvis rotation) measured for these candidates (candidates 2,3 in Fig: 4.17(b)) for right foot are minimal than the other candidates though they had prosthesis on different sides. The data in Fig: 4.15(e),(f) illustrate that the pelvis rotation along the Y-axis and Z-axis is opposite for the right and left foot, i.e., each side of the pelvis rotates clockwise (up the pelvic obliquity, Fig: 4.8(d)) along the Z-axis and anti-clockwise (external rotation, Fig: 4.8(b)) along the Y-axis, and vice versa. The simultaneous movement of the left and right hips during the walking stance and swing phase causes this behavior. However, candidate 1 (Fig: 4.15(e),(f)) did not showcase a similar trend. This candidate pelvic rotation is in the same direction during the heel-strike event. The anterior and posterior pelvic tilt (Fig: 4.8(a)) indicates differing patterns (Fig: 4.15(d)) for each participant. Also, no strong correlation is seen with the other pelvic rotations along the Z-axis and Y-axis. Also, the standard deviation marking (black vertical line) in Fig: 4.15, 4.16, 4.17 indicate the measured values are very unconstant during walking, i.e., they differ a lot for each heel-strike event.

[5] Mean and standard deviation (black vertical line) calculated for 20 consecutive steps

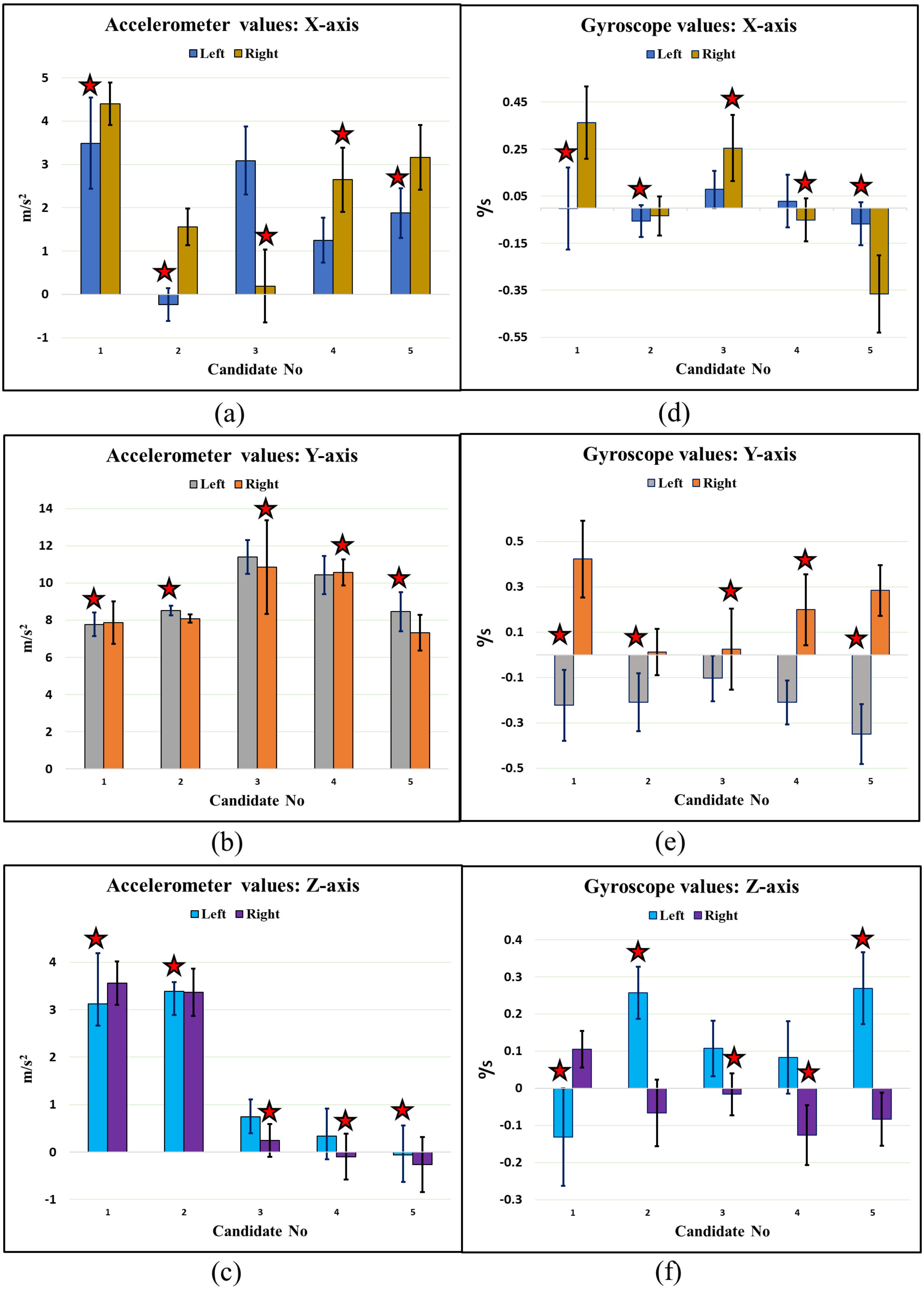
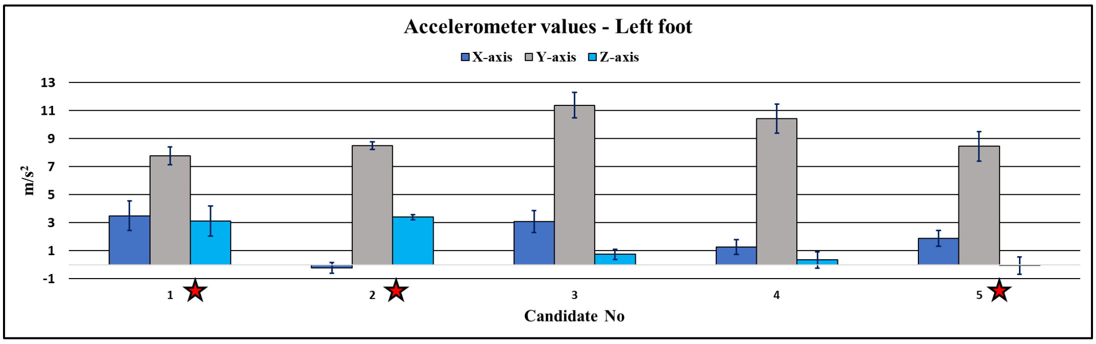
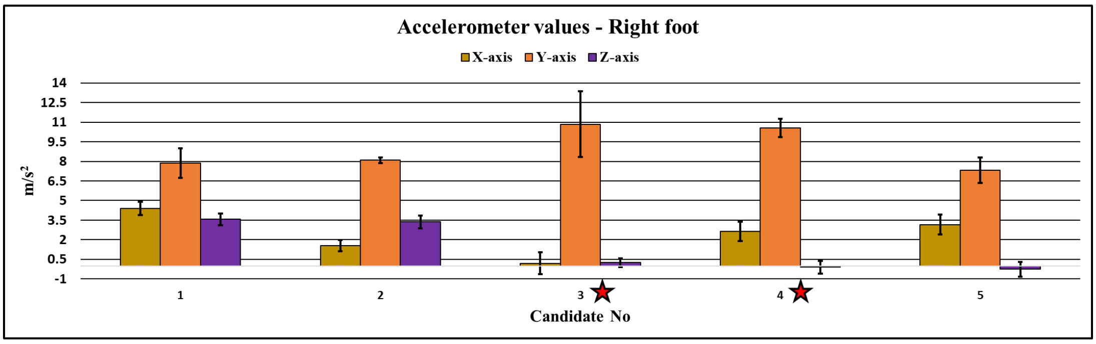


Figure 4.15: With hip prosthesis - Linear accelerations and angular velocities measured during left and right foot heel-strike event

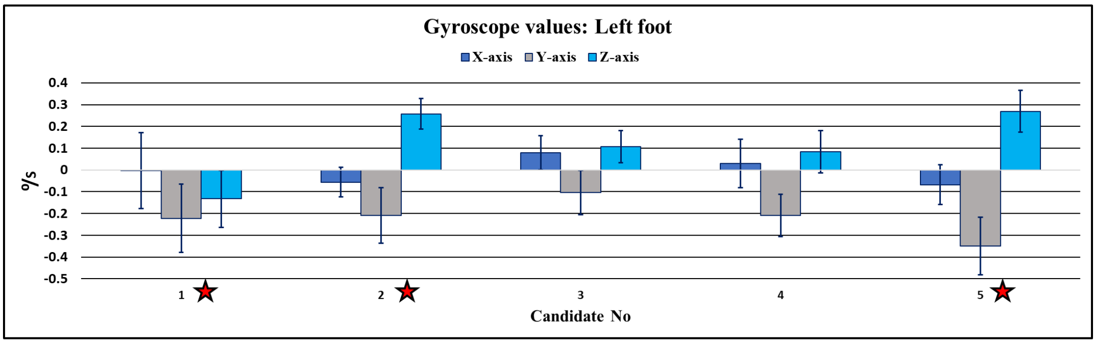


(a)

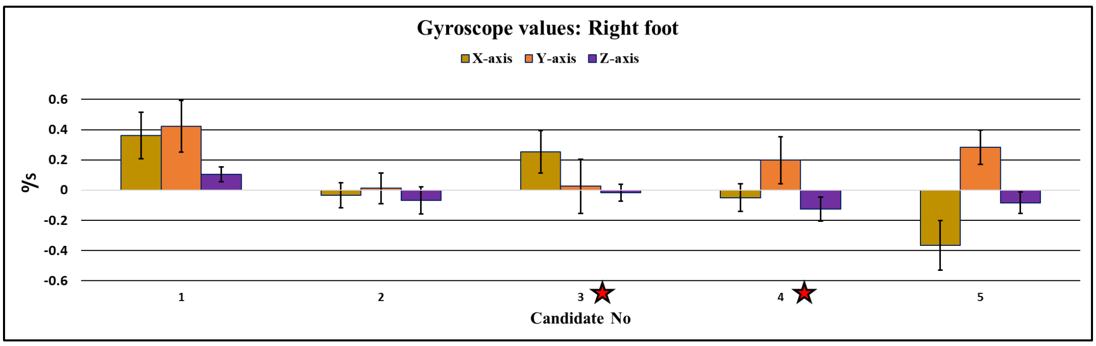


(b)

Figure 4.16: With hip prosthesis - Linear accelerations measured during (a) left foot heel-strike event (b) right foot heel-strike event



(a)



(b)

Figure 4.17: With hip prosthesis- Angular velocities measured during (a) left foot heel-strike event (b) right foot heel-strike event

4.4.2 Knee Prosthesis

Fig: 4.18, 4.19, 4.20 presents the values recorded for linear accelerations and angular velocities for all the participants[6] with knee prosthesis. The red stars on the figures indicate the side (left or right) of the prosthesis present for that participant's knee. Fig: 4.18 correlates the accelerations and velocities caused during the heel-strike event in the left and right foot for all the participants. This figure presents how the same person's accelerations and angular velocity values differ during right and left foot heel-strike events. Whereas, Fig: 4.19, 4.20 contrasts the accelerations and velocities measured for the participant's left and right foot heel-strike event. These figures display all the participants accelerations and angular velocity values generated for the left foot and right foot, respectively. It also illustrates how each walking style matches/differs with the rest of the participants w.r.t left/right foot.

The values from the figures explain the acceleration and velocity values will primarily differ for left and right foot for the same participant. Also, these accelerations values and velocities differ for each participant. The accelerations measured for right and left foot along Y-axis are in the range of $7.5m/s^2$ to $10m/s^2$ (Fig: 4.19) whereas the other two axes recorded in between $1m/s^2$ to $3m/s^2$. This observation indicates that the participants have different values during the transition from the stance phase to the swing phase. Moreover, it also illustrates every participant has (Fig: 4.18(a),(b),(c)) linear acceleration of one foot higher than the other foot along *X, Y, Z-axis*. Also, some candidates (candidates 1,2,3 in Fig: 4.18(c)) have less accelerations along Z-axis than the other candidates.

The pelvis movement (measured by gyroscope along *Z-axis* and *Y-axis*) indicate some individuals (candidate 1 in Fig: 4.18(e), candidates 1,2,3,5,6 in Fig: 4.18(f)) where they are exhibiting pelvis rotation in only one direction during the heel-strike event,i.e., the pelvis is rotated in the same direction for both foot heel-strike events. Plus, the angular velocities measured for some candidates (candidates 3,5 in Fig: 4.18(e)) for one foot are minimal than the other candidates. This indicates that the candidates pelvis rotation is more for one foot at the heel-strike event than the other foot heel-strike event. The anterior and posterior pelvic tilt (Fig: 4.8(a)) indicates differing patterns (Fig: 4.18(d)) for each participant. Also, no strong correlation is seen with the other pelvic rotations along the Z-axis and Y-axis. Finally, the standard deviation marking (black vertical line) in Fig: 4.18, 4.19, 4.20 indicate the measured values are very unconstant during walking, i.e., they differ a lot for each heel-strike event.

[6] Mean and standard deviation (black vertical line) calculated for 20 consecutive steps

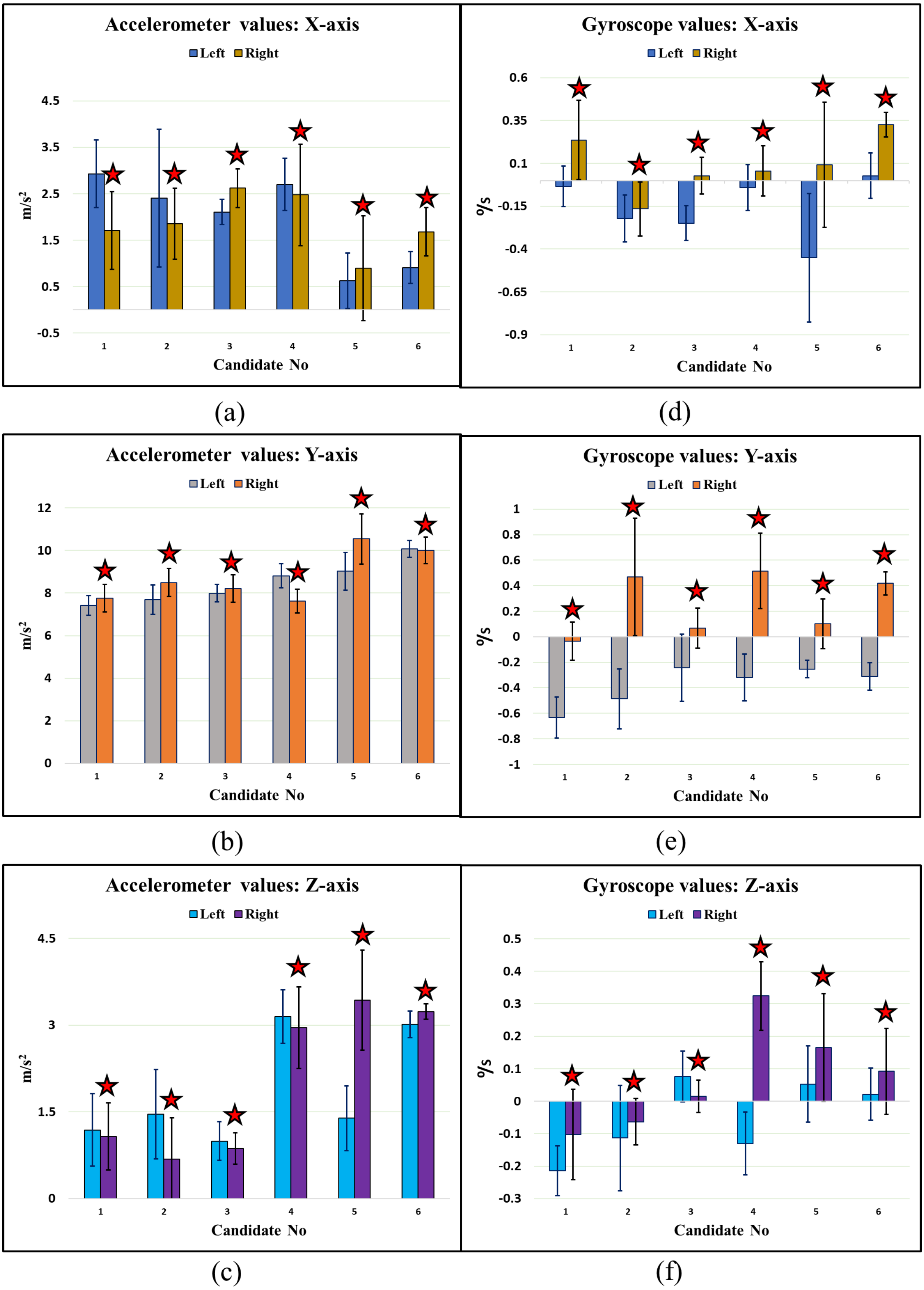
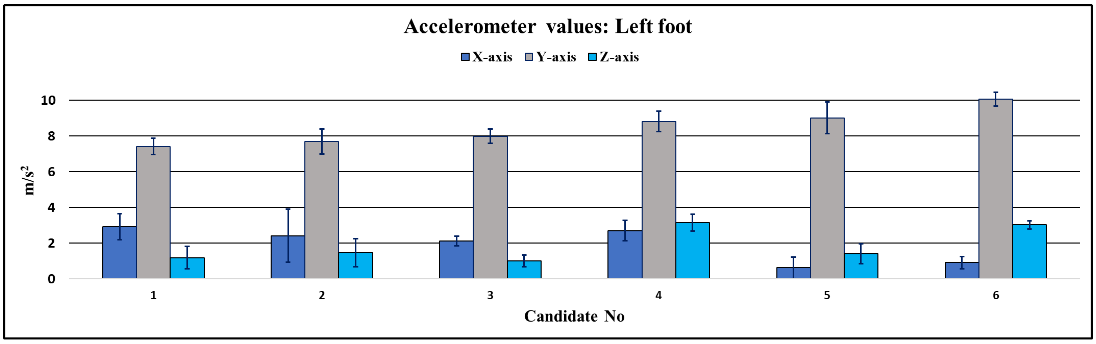
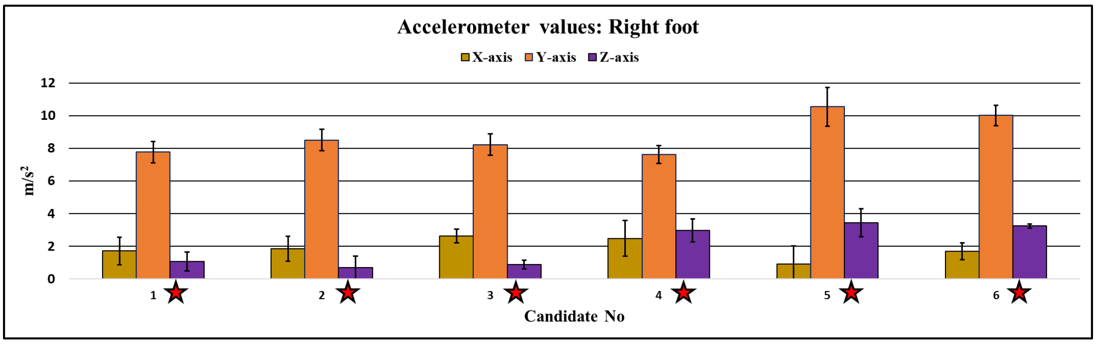


Figure 4.18: With knee prosthesis - Linear accelerations and angular velocities measured during left and right foot heel-strike event

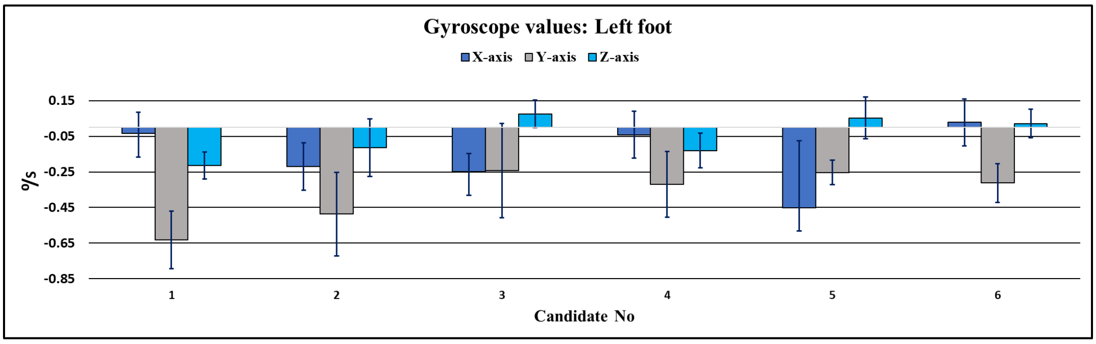


(a)

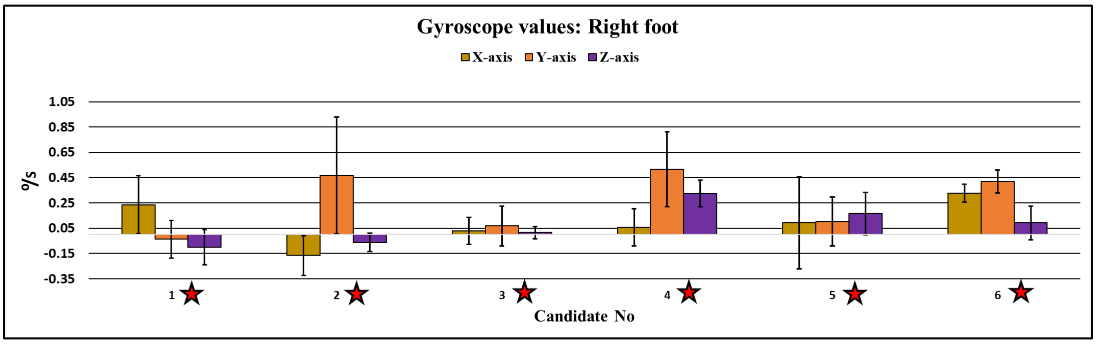


(b)

Figure 4.19: With knee prosthesis - Linear accelerations measured during (a) left foot heel-strike event (b) right foot heel-strike event

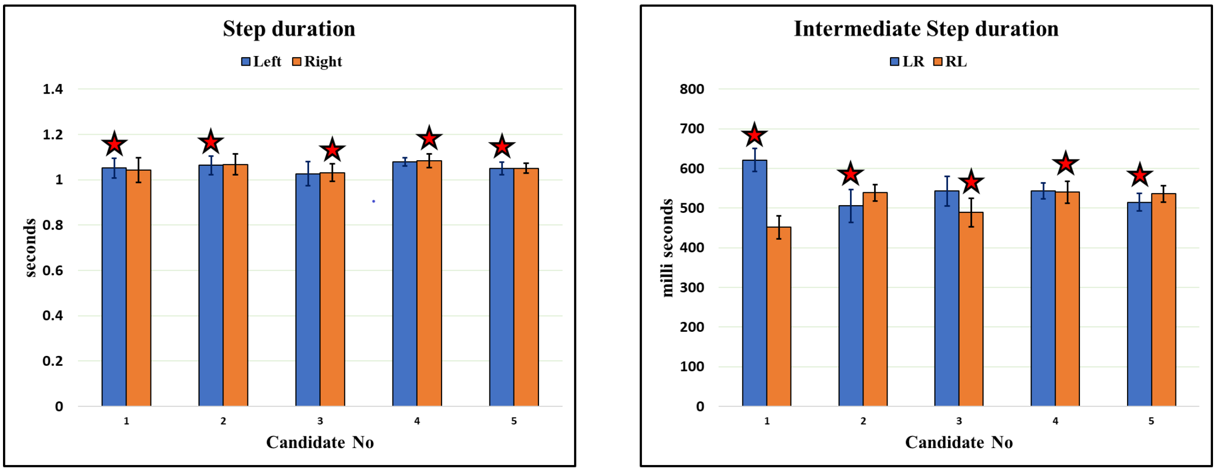


(a)



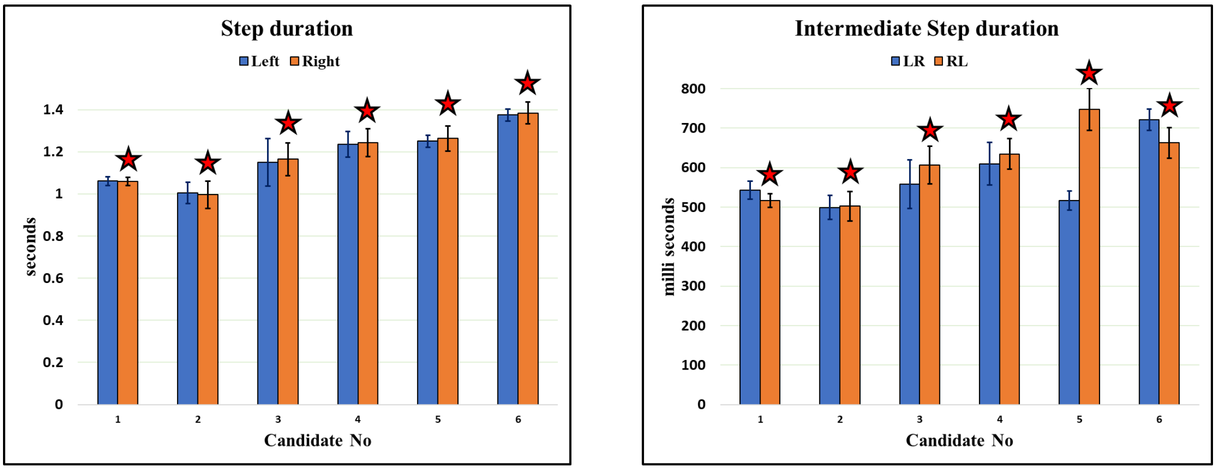
(b)

Figure 4.20: With knee prosthesis - Angular velocities measured during (a) left foot heel-strike event (b) right foot heel-strike event



(a) (b)

Figure 4.21: With hip prosthesis - (a) Step duration (b) Intermediate step duration



(a) (b)

Figure 4.22: With knee prosthesis - (a) Step duration (b) Intermediate step duration

The heel-strike events identified with the help of pressure sensors are used to calculate the step-duration and intermediate duration between right-left (RL) and left-right (LR) feet. Fig: 4.21(a) presents the step duration, and Fig: 4.21(b) presents the intermediate step duration measured for all the participants with a hip prosthesis in the experiment[7]. Whereas, Fig: 4.22(a) presents the step duration and Fig: 4.22(b) presents the intermediate step duration measured for all the participants with knee prosthesis in the experiment[7]. This data showcases that step duration *(both legs)* for the majority of the participants is $\approx 1sec$ (Fig: 4.21, 4.22). Furthermore, the intermediate step duration is relatively equal for right-left and left-right feet for the participants with hip and knee prostheses. However, there are participants (candidates 4,5,6 in Fig: 4.22(a)) whose step duration is $\approx 10\% \ to \ 20\%$ higher than the usual. Similarly, these participants have higher intermediate step duration values (Fig: 4.12(b)). The probable reason for these measurements is

[7]These calculations are performed manually for twenty-eight consecutive steps from the collected data.

that the participants have more extended legs/taller or walk slightly faster than others. Overall, the participants with hip and knee prostheses maintain similar values for the step duration and intermediate step duration.

The linear accelerations measured for both participants with and without prostheses showcased similar values with slightly lower Y-axis accelerations for participants with a prosthesis (Fig: 4.10, 4.19). However, more differences are detected in the angular velocities where the participants with knee prosthesis showcased they do not move their hips equally in both directions. Instead, they tend to shift it in the same direction for both feet heel-strike events. Furthermore, the intermediate step duration between participants with and without prostheses showcased similar results. This observation negates our original hypothesis: ***Hypothesis -*** *The intermediate step duration differs significantly for the users with a prosthesis in the hip/leg in comparison to the users without a prosthesis.* Therefore, the intermediate step duration might not be the primary criteria to distinguish whether walking is symmetric and asymmetric. However, other walking parameters in the swing and stance phases have been unexplored in this study. Moreover, the patterns generated for the gyroscope between the two heel-strikes are diverse, indicating the differences in walking during the stance and swing phase as a group rather than targeting one specific parameter in the stance phase (heel-strike event). Overall, the walking patterns and acceleration measurements are different *(small-scale)* for users with and without prostheses. At the same time, the step duration and intermediate step duration for users with and without prostheses are almost similar and display no considerable difference to distinguish them.

Chapter 5

Real-Time Algorithm

This chapter focuses on the methods/approaches used in developing a real-time processing algorithm. The algorithm developed from observing sensor signals *(during the heel-strike event)* will be referred to as the Straight Forward Data Analysis Method for the rest of the report. This method is developed based on the idea formulated in hypothesis[1 2]. However, after the results from the previous chapter are not supporting this idea/criteria (intermediate step duration) for distinguishing the type of walking, an alternate method is considered. The primary focus in the straight forward analysis relied on only heel-strike events in the stance phase, but there are many other events in the stance and swing phases of walking. Hence, the machine learning approach is preferred to utilize the available additional parameters in the walking activity. The machine learning approach is referred to as the Machine Learning Approach for the remainder of the report.

5.1 Straight Forward Data Analysis Method

The walking patterns recorded for users with and without prostheses presented specific acceleration peaks generated at the heel-strike event during walking activity *(along Z-axis and Y-axis during the heel-strike event)*. Presently, with the help of these peaks, the identification of intermediate step duration is possible. However, this process needs to be done in real-time, introducing an increased challenge of predicting the occurrence and identifying the peaks.

Goal of this method is to distinguish the walking performed by a user is symmetric or asymmetric. This method's decisive factor/criteria is the time duration between two consecutive heel-strike events (intermediate step duration).

[1] ***Hypothesis:*** *The intermediate step duration differs a lot for the users with the prosthesis in the hip/leg, unlike the users without prosthesis.*

[2] The development of this algorithm is initiated during the pre-study phase of the thesis (Fig: 1.1)

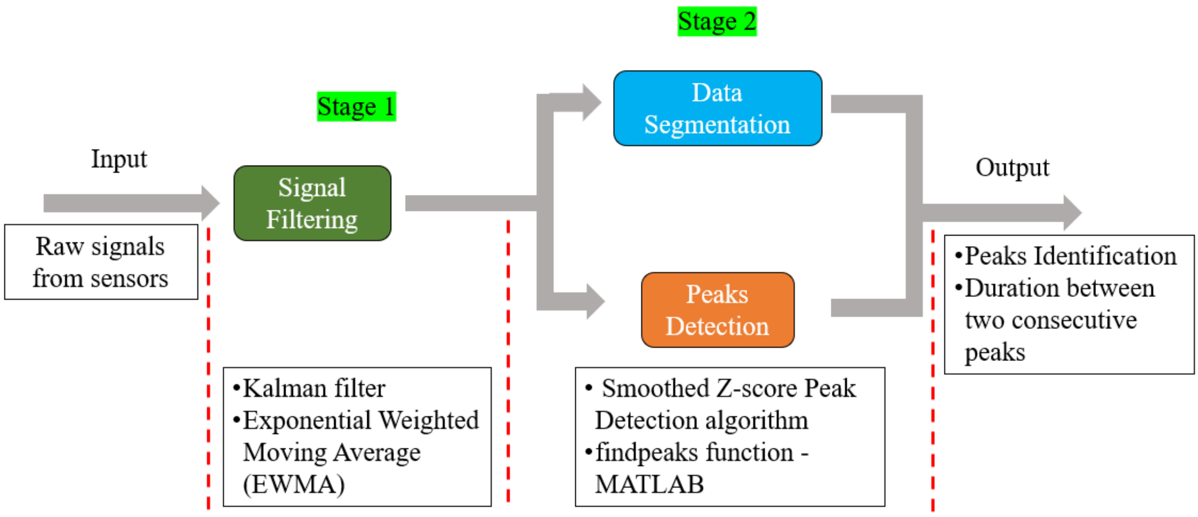


Figure 5.1: Straight Forward Data Analysis

Fig: 5.1 presents the idea of the Straight Forward Data Analysis algorithm. This method contains two stages of implementation. The first stage focuses on reducing the noise from the raw sensor signals or smoothening the sensor signals. In comparison, the second stage works on data segmentation and identifying the peaks present in the filtered signal. Since accelerometer data arrives in a continuous stream, data segmentation is necessary. This is because accelerometers provide instantaneous measurements, either when requested or at periodic intervals. The continuous data flow must be split into smaller segments/windows for additional processing to discover the peaks that reflect the heel-strike event. Moreover, the segment/window size of the operation can be experimented with within this stage to derive the duration between two consecutive peaks. The below sections explain in detail the development process of these stages.

5.1.1 Signals Filtering

Goal of this stage 1 is to generate a smooth signal from the raw signals obtained from sensors. Also, to maintain the peaks generated during the walking activity. The Kalman filter and exponential weighted moving average (EWMA) methods have been implemented for the raw signals from the sensors.

Procedure

Kalman Filter

The obtained raw signals from the sensor measurements are processed through the two filtering algorithms to eliminate the noise and determine better peaks in walking activity. The Kalman filter provides an optimal/estimated sensor reading from a noisy measurement [38]. These noisy measurements are added to the measurement system by the surrounding environment or external factors. This filter aims to estimate the system values by eliminating the noises present. In this scenario, it tries to estimate the accelerations measured by the IMU sensor. This elimination of noises is carried out by a recursive process of predicting the next input to the system and calculating the system's output. The prediction of the next input relies on the weights. The weights are computed from the covariance, a measure of the estimated uncertainty of the prediction of the system's input. The responsiveness of the filter is provided by the Kalman filter's gain (κ). The Kalman gain represents the relative weight assigned to measurements and current state estimates, and it may be adjusted to obtain a particular result.

Fig: 5.2 represents the recursive operation of the Kalman filter. The input measurements are updated (*update estimate*) with initial Kalman gain values. Next, the covariances are updated (*update covariance*) and utilized to obtain the new Kalman gain value. The new Kalman gain factor is used in estimating the output measurements from the input measurements. This recursive process of estimating the output measurements is performed for every input.

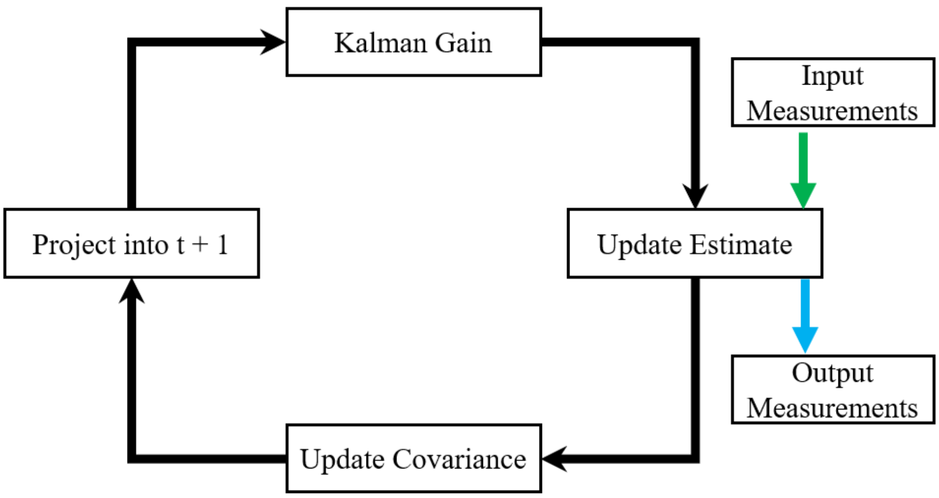


Figure 5.2: Kalman Filter Recursive Algorithm

The Kalman filter (*mathematical implementation*) is designed by considering the system model as: $x_{t+1} = \phi_t + w_t$, sensor model as: $y_t = H_t x_t + v_t$, estimate of $x_t = \hat{x}_t$, $\hat{x}_t'$ is the previous estimate of x_t, P represents the error covariance between $x_t, \hat{x}_t$, P_t' is the previous estimate of P_t, κ_t as Kalman gain ,$Q = Cov(w)$, and $R = Cov(v)$. Where Cov stands for covariance, w_t is process noise, v_t is observation noise, subscript t indicates the values of different variables at time t and assuming H, ϕ are constant (linear filter). The Table: 5.1 represents the filter implementation for the sensor signals in real-time. In this process x_t represents the accelerometer input coming from the IMU and $\hat{x}_t$ is the estimated output measurement. The mathematical relation between x_t and $\hat{x}_t$ is seen in Update Estimate equation (*Table: 5.1*). Whereas, the remaining equations in the table present the intermediate steps performed to obtain the output measurements *(error covariance update and Kalman gain update)*.

Description	Equation
Kalman Gain	$\kappa_t = \frac{P_t^{'} * H}{H * P_t^{'} * H + R}$
Update Estimate	$\hat{x}_t = \hat{x}_t^{'} + \kappa_t * [x_t - H * \hat{x}_t]$
Update Covariance	$P_t = (1 - \kappa_t * H) * P_t^{'}$
Project into $t+1$	$\hat{x}_{t+1}^{'} = \hat{x}_t$ $P_{t+1} = P_t + Q$

Table 5.1: Kalman Filter Recursive Algorithm Equations

Exponential Weighted Moving Average (*EWMA*)

A moving average is a statistical computation that analyzes data points by calculating the averages of different subsets of the entire data set. A moving average is frequently employed with time-series data to smooth out short-term variations while highlighting longer-term trends or cycles. A moving average is a form of convolution in mathematics; therefore, it may be considered a low-pass filter in signal processing [67]. A weighted average is an average that uses multiplying factors to provide data at various points in the sample window varying weights. The weighted moving average is the convolution of data with a defined weighting function in mathematics. The EWMA acts as a first-order infinite impulse response filter because applying exponential weights on the moving average calculations. The EWMA filter smoothens the time series data by using the exponential window function. Unlike moving average filters where the previous observations are weighted equally, the weights are decreased over time with the help of exponential functions in this filter. The following equations are used to implement this filter for the sensor data measured by the IMU.

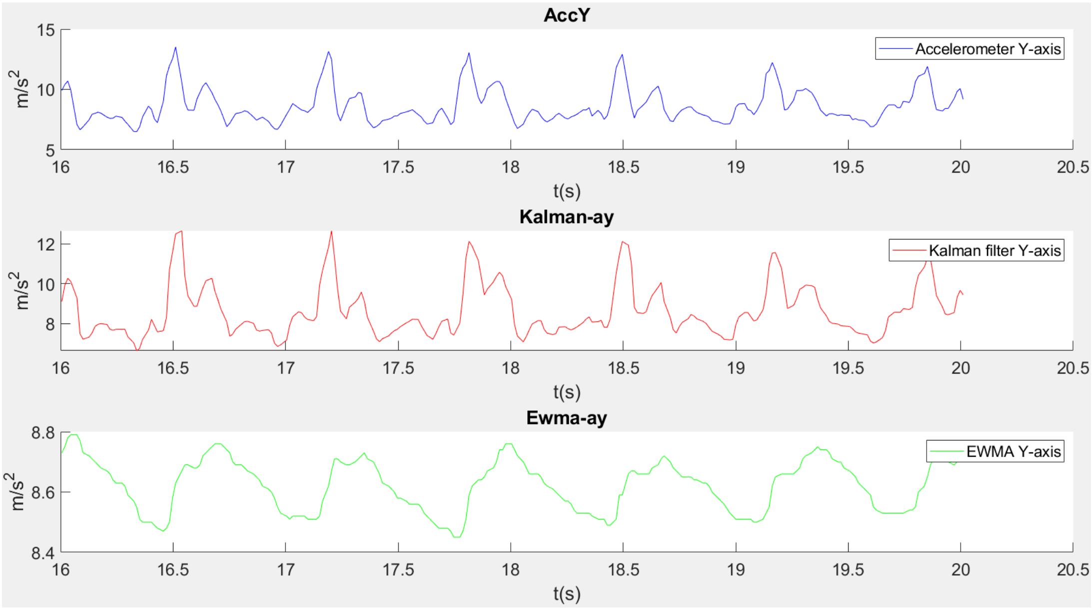
$$s_0 = x_0 \tag{5.1}$$

$$s_t = \alpha x_t + (1 - \alpha) s_{t-1}, t > 0 \tag{5.2}$$

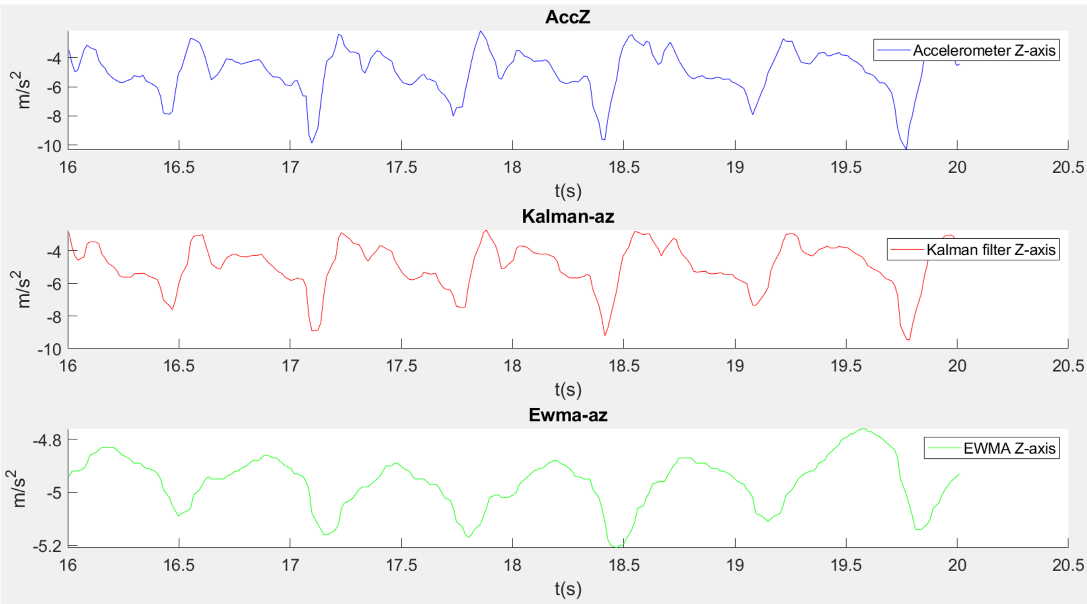
Where t is time, x_t is raw data at time t, s_t is the output of the smoothing algorithm at time t, and α is the smoothing factor ($0 < \alpha < 1$). The raw input sensor signal is smoothened by considering the previous smoothened output signal and the exponential smoothing factor. The equation 5.2 represents the relation of the raw input sensor signal (x_t) and smoothened output sensor signal (s_t).

Observation

Fig: 5.3 illustrates the output of both Kalman and EWMA filters during real-time processing. The EWMA filter has demonstrated much effectiveness for the current idea to smoothen the signal. Also, the output tries to match the peak shape, making it more convenient for the peak processing algorithm. In comparison, the Kalman filter output does not satisfy this requirement. In addition, both filters introduce a delay in reproducing peaks. This can be identified in Fig: 5.4 and Fig: 5.5. This delay is presented clearly in Fig: 5.5 for EWMA filter output. In this figure, the green cross marking indicates the peaks formed in raw signal and filtered signal. There is a delay of δT between the peaks formed in raw signal and filtered signal. The value of this delay is the range of *1* or *2* sample points which is *19.23ms* or *38.36ms (Data collection frequency - 52Hz)*. Also, the peak values *(accelerometer measurements)* in Kalman filter output closely match the raw signal peak values, but it is not a similar case for the peak values generated in EWMA filter output. This is due to the exponential weighted average functionality in EWMA. This behavior can be observed in the Fig: 5.3(a),(b) m/s^2 in y-axis. However, the EWMA filtered signal smoothens the unnecessary peaks in the raw signal with good results, whereas the Kalman filter could not do it in this scenario. Overall, EWMA implementation is considered for this approach because the output is more suitable for the succeeding stage of implementation, i.e., peak detection.



(a) Y-axis



(b) Z-axis

Figure 5.3: *Blue* is raw signal, *Red* is Kalman filter output, *and Green* is EWMA filter output

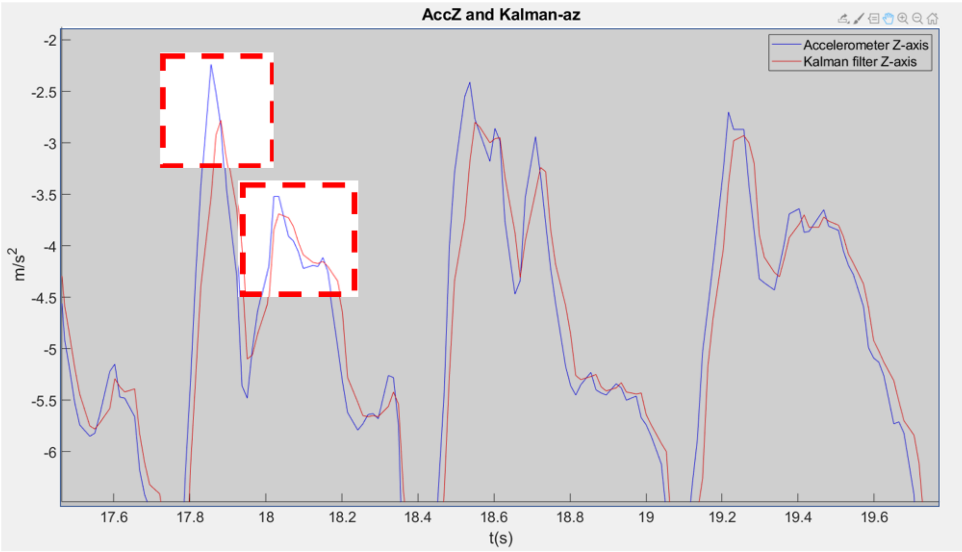


Figure 5.4: Kalman filter output- signal shape and delay observation

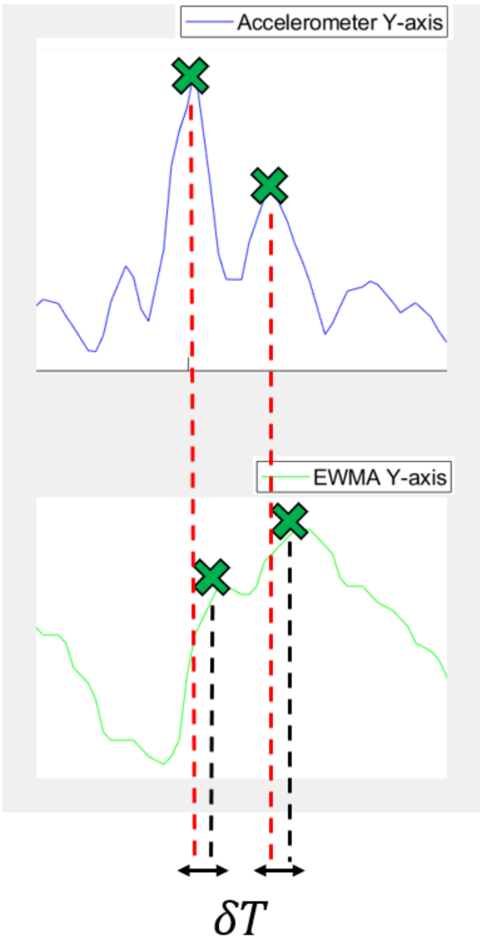


Figure 5.5: EWMA fliter output - signal shape and delay observation

5.1.2 Peaks Detection

Goal of this method is to identify peaks present in the filtered signal output.

Procedure

Smoothed Z-score Peak Detection

The smoothed z-score technique was developed mainly for real-time signal processing applications to achieve robust and adaptive peak identification. Using a sliding window, the method scans a series of data points and calculates the moving mean and standard deviation. A moving mean computation is a method of analyzing data points by calculating the averages of various subsets of the entire data set. The positions with a z-score over a certain level are considered peak. The Smoothed Z-score Peak Detection algorithm tracks the signal's trend with a moving mean and creates a threshold around the signal with a deviation. The algorithm identifies the points that are outside of the threshold as peaks. The concept of dispersion is implemented: a data point is defined as a peak if the gap between it and the mean is more significant than a specific amount of standard deviations [28].

```
# Let y be a vector of timeseries data of at least length lag+2
# Let mean() be a function that calculates the mean
# Let std() be a function that calculates the standard deviaton
# Let absolute() be the absolute value function

# Settings (choose what is best for your data)
set lag to Lag;              # Lag is for the smoothing functions
set threshold to Threshold;  # Threshold is for the standard deviations for signal
set influence to Influence;  # between 0 and 1, where 1 is normal influence, 0.5 is half

# Initialize variables
set signals to vector 0,...,0 of length of y;     # Initialize signal results
set filteredY to y(1),...,y(lag)                  # Initialize filtered series
set avgFilter to null;                            # Initialize average filter
set stdFilter to null;                            # Initialize std. filter
set avgFilter(lag) to mean(y(1),...,y(lag));      # Initialize first value
set stdFilter(lag) to std(y(1),...,y(lag));       # Initialize first value

for i=lag+1,...,t do
if absolute(y(i) - avgFilter(i-1)) > threshold*stdFilter(i-1) then
    if y(i) > avgFilter(i-1) then
    set signals(i) to +1;                        # Positive signal
    else
    set signals(i) to -1;                        # Negative signal
    end
    set filteredY(i) to influence*y(i) + (1-influence)*filteredY(i-1);
else
    set signals(i) to 0;                          # No signal
    set filteredY(i) to y(i);
end
set avgFilter(i) to mean(filteredY(i-lag+1),...,filteredY(i));
set stdFilter(i) to std(filteredY(i-lag+1),...,filteredY(i));
end
```

Figure 5.6: Pseudocode [28]

Fig: 5.6 presents the pseudocode of this method. The parameters required in this operation are supposed to be set according to the type of data used by this filter. Three parameters are operated in the algorithm: *lag* (l), *influence* (I_n), and *threshold* (th). In this scenario, the filtered signal (x_i) from the EWMA filter is provided to this filter. The provided data is then processed in batches (might refer to data segmentation section) *(by collecting few samples at a time)*. The initial mean and standard deviation are calculated as per equations 5.6 5.7 for each batch depending on the lag parameter. The output of the filter (y_i) is calculated as 5.10. This is obtained by comparing the value from 5.9 (z-score) to the threshold (th) value set according to our data. If a peak is detected, the mean is updated by 5.8 by considering the influence factor (I_n). This process is recursive *(for loop)*, as seen in the pseudocode.

$$\bar{\mu}_i = \frac{1}{l} \sum_{i}^{i+l} \mu_i \tag{5.6}$$

$$\sigma_{\mu_i} = \sqrt{\frac{\Sigma_i^{i+l} (\mu_i - \bar{\mu}_i)^2}{l-1}} \tag{5.7}$$

$$\mu_i = I_n x_i + (1 - I_n)\, \mu_{i-1} \tag{5.8}$$

$$z_i = \frac{x_i - \bar{\mu}_{i-1}}{\sigma_{\mu_i}} \tag{5.9}$$

$$y_i = \begin{cases} \pm 1 & \text{if } |z_i| \geq th \\ 0 & \text{if } |z_i| < th \end{cases} \tag{5.10}$$

The latency determines how adaptable the algorithm is (in terms of the long-term average of the data) and how smooth the data will be. The lag will improve the algorithm's resilience. The algorithm will adjust to the trend for every *50* samples if the latency is set to *50*. The signal's impact on the threshold is referred to as the influence. Influence *0* denotes the data have no bearing on the threshold (that assumes stationarity). The influence should be set between *0 and 1* if the signal is not stationary and containing peaks. Signals with a *0.1* impact have *10%* of the influence that regular data points have on the threshold. It's the difference between the moving mean and the number of standard deviations. This parameter will determine the algorithm's sensitivity.

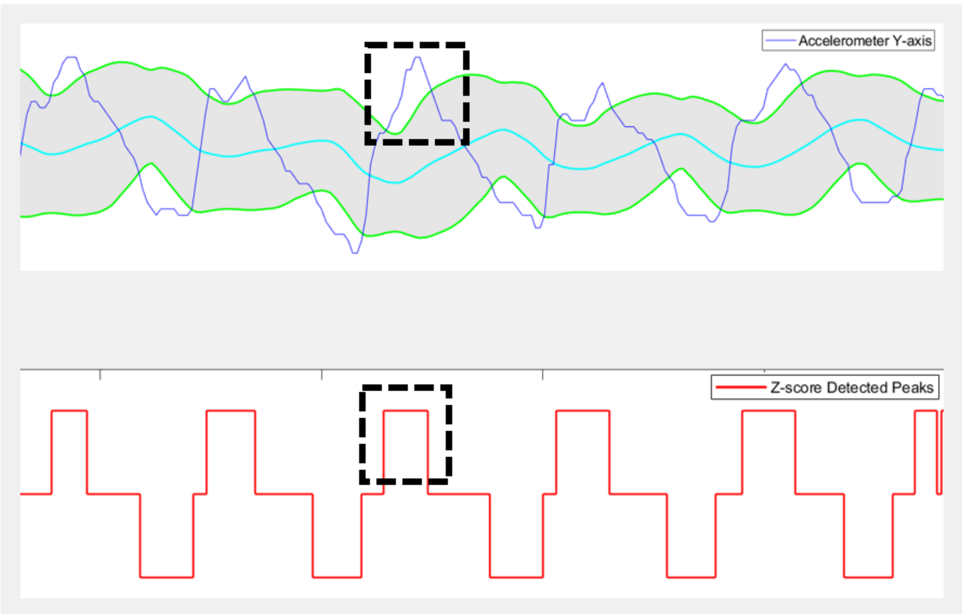


Figure 5.7: Z-score peak detection output

Fig: 5.7 illustrates the output of the Z-score peak detection method for offline[3] implementation. The cyan color line in the top graph indicates the moving mean of the filtered signal *(Accelerometer Y-axis)*. At the same time, the green lines indicate the threshold values on the positive and negative sides of the average. This image showcases how the threshold changes relative to the moving average. The bottom graph presents the peaks identified for the given input. The black box highlighted in the top and bottom graphs exhibits the positive peaks identified when the input signal is above the threshold value.

findpeaks-MATLAB algorithm

The findpeaks© function from MATLAB[4] achieves local peaks in the given the set of data. The local peak is defined as a data sample that is larger than the two neighboring samples or equal to infinity. Fig: 5.8 presents the peaks identified in offline[3] implementation to the same input provided to the Z-score Peak Detection algorithm. The black square box is highlighted in the image to indicate the identified peak by the findpeaks function.

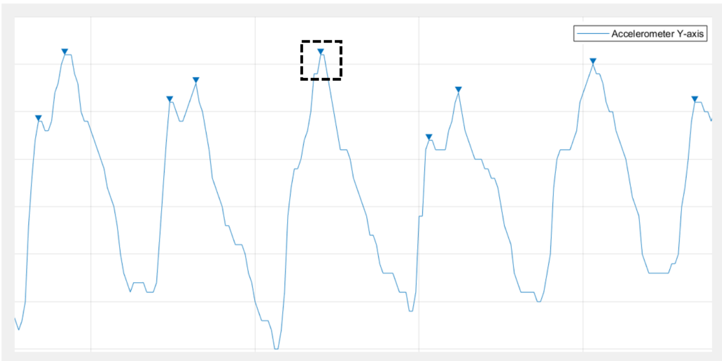


Figure 5.8: findpeaks- MATLAB algorithm output

Observation

The outputs generated by the Z-score Peak Detection algorithm and findpeaks function MATLAB, the findpeaks function illustrated better peak identification for the same filtered signal input. Thus demonstrating usage of this function can represent a more preferred option to implement in a real-time process to identify peaks. Though the Z-score Peak Detection Algorithm identified the peaks, determining the exact point where a peak is achieved looked delicate and can introduce complexity in determining the time duration between two consecutive peaks. In comparison, the findpeaks function output looks convenient in obtaining the time duration between two successive peaks. Hence, the findpeaks function demonstrated better results to the goal of this peak detection method. However, the real-time implementation of this filter needs segments of the continuous data to be provided at specific intervals to identify the peaks. This interval selection for segments of data to implement in real-time is explained in the section 5.1.3. In addition, this function is converted to c/c++ language from MATLAB by using the code builder feature in MATLAB. The preceding statement creates an impression of a straightforward

[3] The outputs are generated by post-processing

[4] *https://www.mathworks.com/help/signal/ref/findpeaks.html*

task. But the management of the generated function looked tricky. Understanding the custom data types used by the code builder to generate a c/c++ code is not a routine thing. It demanded some effort in integrating this custom function in MATLAB to an Arduino IDE environment.

5.1.3 Data Segmentation

Goal of this method is to provide segments of accelerometer data to peak detection methods to calculate the time duration between two peaks or alternate peaks. Ultimately, this time duration represents the intermediate step duration of a user walking utilizing this device.

The continuous data flow coming from the IMU must be split into smaller data segments/windows. These smaller data segments are provided to the peak detection algorithms to identify the peaks that reflect the heel-strike event. However, it is tough to segment a continuous data flow. One of the most challenging aspects of accelerometer data segmentation is dividing the continuous data stream into a group of discrete segments best suited for activity identification [7][21]. Moreover, the user appears to conduct a series of walking steps likely interleaved rather than divided by pauses. On the other hand, defining the precise bounds for a heel-strike event for a walking activity is challenging.

The effectiveness of feature extraction and inference algorithms is significantly influenced by the appropriate selection and parameterization of segmentation techniques, resulting in the accuracy of identifying the peaks generated during the heel-strike event. The continuous data flow obtained by accelerometers is divided into windows with either static or dynamic sizes. For this report, two segmentation algorithms are of interest: Fixed-size Non-overlapping Sliding Window (FNSW) and Fixed-size Overlapping Sliding Window (FOSW) [32][30]. Because FNSW is a straightforward segmentation method with no data overlap, the number of windows may be precisely determined. However, because this method uses a set window size, data linked with a particular event, like a heel-strike event, maybe split over many windows, resulting in significant information loss. FOSW comprises data overlap between adjacent windows. The overlapping between two windows is referred to as window shifts and defined in percentages, i.e., 10%, 20%, etc., overlap. In the static approach size of the window is set by either a fixed number of samples or a varying number of samples recorded in specified time duration. Whereas for the dynamic approach, the window size varies in real-time according to certain triggering conditions set.

The data segmented (FNSW/FOSW) from continuous data flow is further is processed with an event detection algorithm. In this report, the Z-score Peak Detection algorithm and findpeaks MATLAB function are the event detection algorithms. The event detection algorithms can be either classified as online (real-time) or offline (post-processing). Online event detection algorithms aim to process a set of data points before moving on to the next set, with the number of new data points in subsequent sets being determined by the target application and available computer resources. In the offline scenario, data is first gathered and processed to discover event points with less emphasis on computing resource needs. Online event detection algorithms are sequential, quick, and reduce false alarms; offline event detection algorithms aim to discover all potential change points to achieve better levels of sensitivity (true positives) and specificity (fewer false alarms) (true negatives). Table: 2.2 from the literature reading showcases the authors implementing these online and offline event detection algorithms for various activities. Moreover, there are many studies in determining multiple human activities (running, sitting, etc.) or transition of activities (sitting to standing, standing to lying, etc.) using the same online and offline detection algorithms [52][23][80]. They use change detection algorithms to identify locations within an input data stream that exhibit sudden changes in metrics like mean or variance, thus representing a change point in time series data [8]. However, these methods are not directly applicable for this report as the area of interest is to identify peaks performed by a solo activity rather than multiple transitions of activities.

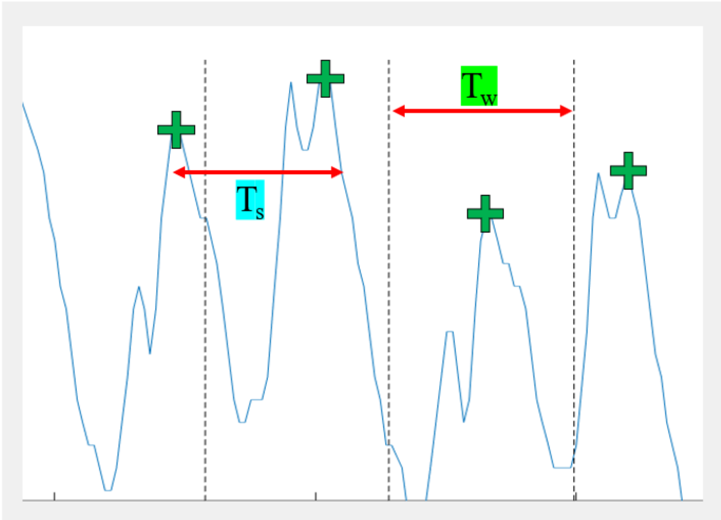


Figure 5.9: Peak detection in real-time using static FNSW

The Z-score Peak Detection algorithm and findpeaks MATLAB functions are capable of executing offline and real-time processes. The real-time execution of these event detection algorithms is possible by implementing static and dynamic FNSW/FOSW approaches for the data segmentation method to the continuous data coming from the IMU. Firstly, the EWMA filter from the stage 1 output is segmented using a static FNSW algorithm with window duration (T_W) as 600ms. The findpeaks function processes the filtered data from the EWMA filter for every 600ms to identify the peaks. This entire process is deployed on the device constructed in Chapter 3 (second development). *During this deployment, the pressure sensors are removed from this device as they are unintended towards the wearable device goals of this report.* Fig: 5.9 represents the output of the EWMA filter (blue), static FNSW algorithm (black vertical dotted line), and findpeaks function (green marking) when performed in real-time. The T_W represents the window duration, and T_S presents the time duration between two peaks. The overall functioning of all the filters and algorithms has shown encouraging results to implement the dynamic FNSW algorithm for better results. The code for the static FNSW algorithm implementation is available in Appendix: C.

However, the results from chapter 4 (Study) are not supporting the hypothesis. This outcome affects the overall goal of the straight forward data analysis method because the goal is to obtain the intermediate step duration. Hence, the implementation of a dynamic FNSW algorithm is not carried out. Also, verification/robustness of the implemented method (as mentioned in afore paragraph) is not performed for users with and without prostheses. Overall, this straight forward data analysis method which focuses on the duration between two consecutive heel-strike events, will not remain an efficient approach for distinguishing the type of walking performed by the user. Hence, the interest is shifted towards a machine learning approach to explore other events present in the stance and swing phase of walking to determine the type of walking.

5.2 Machine Learning

Machine Learning represents a technology that has seen a rapid increase in popularity and utilization over several years. A vast number of aspirants worldwide are pursuing this technology fast and setting it to diverse uses. The majority of these were implemented for post-processing methods. However, this trend has been shifting towards real-time processing methods in recent years. The processing power/hardware capabilities impose a significant constraint for developing real-time machine learning. For post-processing, a powerful and vast establishment is used (not precisely a device suitable for a wearable/portable solution). Nonetheless, Arduino has launched a modern device named Arduino Nano RP2040 Connect[5] at the beginning of the year 2021 to incorporate machine learning capabilities for real-time applications. This device's size and capabilities fulfill the criteria for a wearable device.

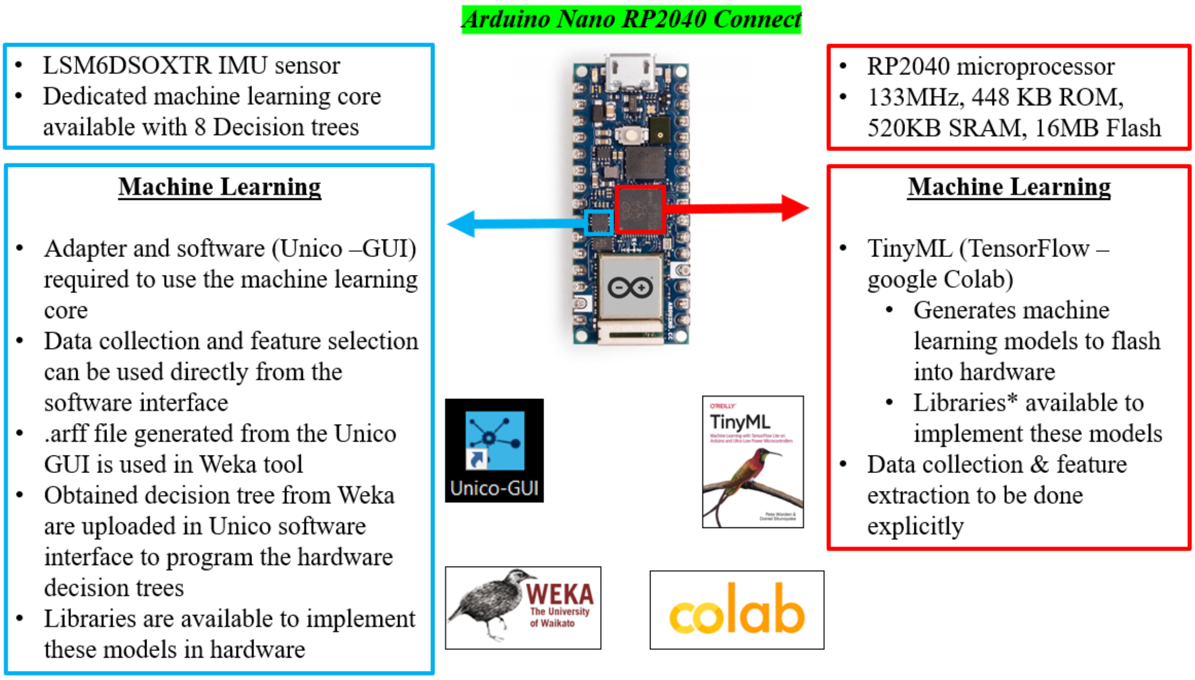


Figure 5.10: Machine Learning - Arduino Nano RP2040 Connect

[5]https://store.arduino.cc/nano-rp2040-connect

Fig: 5.10 presents the two possible machine learning approaches utilizing this device. This device also hosts an inbuilt IMU sensor, i.e., there is no need for an external IMU sensor like MPU6050, which is used in the data collection process of this report. This IMU sensor (LSM6DSOXTR) on the Arduino is capable of hosting eight decision trees. Alternatively, TinyML can be used in developing a machine learning algorithm on the processor. However, both of these implementations are possible with limited operations. This is because either the libraries required to deploy the developed machine learning models on the hardware are not fully developed or not feasible. For the usage of IMU machine learning core, a dedicated hardware[6] and software[7] is required. This software equally comes with limitations like limited feature extraction options and the operating frequency of the machine learning core. The operation frequency of this machine learning core can only be a maximum of 104Hz though the IMU can operate at 1.6KHz. More understanding and usage of this machine learning core are provided here [68].

A binary classification method in machine learning is used to verify the IMU machine learning core's feasibility. The data collected *(raw signals from the sensor)* from all the participants without prosthesis data are labeled as Without Prosthesis (WOP) data, and all participants with prosthesis data are labeled as With Prosthesis (WP) data. In the WOP data set, the candidates showcasing possible asymmetries (section: 4.3) in walking are removed. This adjustment of the data set is performed to have symmetric walking (WOP - after adjustment) and asymmetric walking (WP) data sets, respectively. These data sets are used in developing a binary classifier to distinguish the type of walking performed by the user in real-time. The combination of all these data for each label is put together at random, i.e., one participant's data (each file) is appended with another participant's data. Also, rather than using TinyML, the machine learning core of the IMU sensor is preferred due to the better workflow process and its existing integration with the RP2040 processor. This implementation intends to find a potential machine learning approach achievable in the available hardware capabilities.

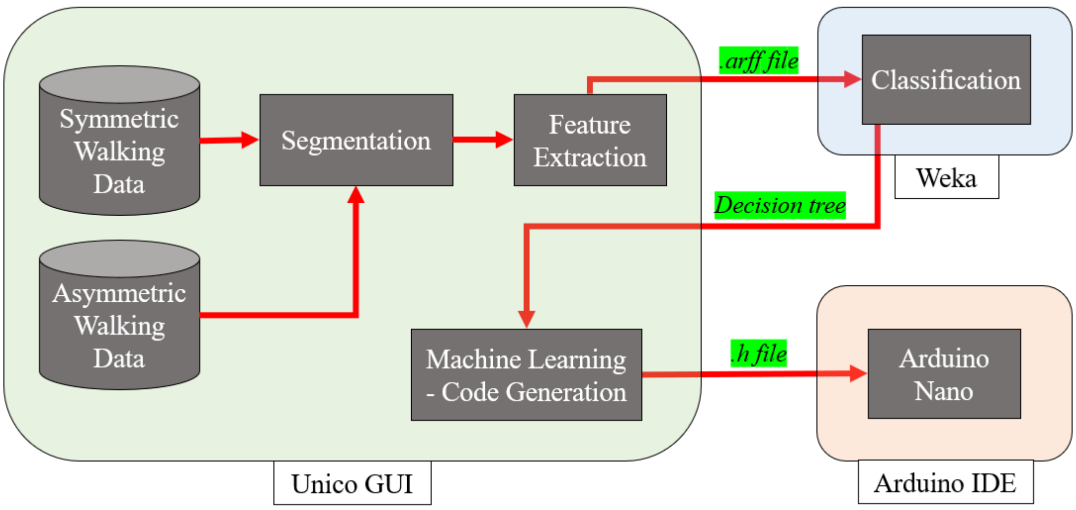


Figure 5.11: Training Procedure

[6]https://www.st.com/en/evaluation-tools/steval-mki109v3.html
https://www.st.com/en/evaluation-tools/steval-mki197v1.html
[7]https://www.st.com/en/development-tools/unico-gui.html

Fig: 5.11 presents the procedure in deriving the classification model (decision tree) from the WOP and WP walking data. This figure also illustrates the operations carried out in various tools. The Unico GUI is responsible for segmentation- segmenting the data with fixed window size, feature extraction- representing a change point in time (mean, variance, etc.) w.r.t segmented data, and machine learning code generation- converting the decision tree into machine learning compatible file. The Weka tool develops a classification model depending on the features extracted from the data *(.arff file)*. The classification model is limited to decision trees because the IMU machine learning core can deploy only decision tree models. Once the decision tree is developed with good accuracy, it is used in the Unico GUI to generate a file deployed on the Arduino Nano. The generated file from the Unico GUI is a *.h* file. The Arduino Nano is capable of reading this file through custom libraries[8] and instruct the IMU machine learning core according to the decision trees developed in the Weka tool. Altogether, three tools are required to create a real-time machine learning model for the IMU machine learning core. However, there are some other alternatives to the Weka tool (MATLAB, Python, RapidMiner), but there is no other alternative for machine learning code generation operation in the Unico GUI.

The implementation of binary classification is performed by implementing variance as the feature extraction method for the labeled data. This feature is computed within a defined samples window during the segmentation process. This window represents the number of samples considered in a time window. The statistical parameters for developing a decision tree are derived by the samples made available in the time window. All the features are computed just once for every window size defined by the user. Hence, defining a proper window size is necessary for getting better binary classification accuracy. Table: 5.2 presents the different window sizes used by other authors for classifying similar activities. Moreover, these authors' offline implementation was to identify the completely different activities like walking, standing, hopping, etc., by using other classification methods in machine learning (Table: 5.2). However, the binary classifier developed in this section focuses on distinguishing the subtle differences present in the same activity. The window sizes selected by various authors in Table: 5.2 are used as a reference for the real-time implementation of the binary classification model. Also, more research is carried out across multiple transition activities that include diverse duration as presented by the authors [6][34]. However, most works usually discard transitional movements due to their generally low incidence and very short durations [59]. Nonetheless, an attempt is committed to identifying these transitional activities with small durations in this section with the help of a binary classification model.

[8] https://docs.arduino.cc/tutorials/nano-rp2040-connect/rp2040-imu-advanced

Ref	Activities	Accelerometer Placements	Classification Accuracy	Window Sizes (in seconds)
[57]	Jogging, running, hopping, jumping, walking, climbing stairs up/down	Waist, thigh, ankle	KNN - 96% with 8 activities; 98% with 3 activities	2
[24]	Walking, running, standing, lying, falling, jumping	Waist belt	HMM-P - 78.8%; HMM-PNP - 80.2%	0.32
[51]	Walking, toddling, crawling, wiggling, rolling	Waist	NB - 73%; BN - 8.8%; DT - 74%; SVM - 86.2%, KNN - 84.1%, J48 - 88.3%, MLP - 84.8%, LR - 86.9%	≈ 2.7
[35]	Walking, jogging, ascending stairs, descending stairs, sitting, standing	Right thigh	Multilayer perceptron - 91.7%	10
[23]	Lying, sitting, standing, walking, lying-standing, standing-lying, sitting-standing, standing-sitting	Chest, left under-arm, waist, thigh	ANN - 96.8%, Decision tree - 96.4%, KNN - 96.2%, Naive bayes - 89.5%, SVM - 92.7%	1

Table 5.2: Window sizes for identifying different activities

Window Size (in sample points)	**154**	**102**	**52**
Window Size (in seconds)	**≈ 3**	**≈ 2**	**1**
Classification Accuracy	**96.9697** %	**95.3177** %	**93.2031** %
Kappa	0.9356	0.9014	0.8566
Mean Absolute Error	0.0474	0.0664	0.0929
Root Mean Squared Error	0.1716	0.2063	0.2426
Relative Absolute Error	9.9935 %	14.0024 %	19.5823 %
Root Relative Squared Error	35.2492 %	42.3746 %	49.8203 %
Size Of the Tree	**9**	**9**	**39**

Table 5.3: Classifier Output- REPTree

Table: 5.3 presents the REPTree classifier output for different window sizes using the variance feature extraction method *(provided in the Unico-Gui tool).* A fold value of 10 is used in Weka to classify the user walking with or without prostheses (asymmetric or symmetric). The classification results by the REPTree classifier present a promising result. The accuracy is higher ($\approx 97\%$) when the window size is 154 samples and output is achieved in $\approx 3sec$. However, when the window size is 102 and 52 samples, the classifier accuracy resulted in $\approx 95\%$ and $\approx 93\%$ respectively. But the output is achieved when the window size is 102 samples is $\approx 2sec$ and $\approx 1sec$ for the 52 samples of window size. Overall, these results show a good detection of user walking (symmetric or symmetric) for the dedicated machine learning core, i.e., for the specific sensor. But, the significant drawback in this implementation is the data sets used for machine learning are unobtained from the IMU sensor present on the Arduino Nano. The data set used in this approach is obtained from the MPU6050 sensor connected to the ESP32 feather board (device constructed in chapter 4). However, the sampling frequency is set to 52Hz, which is equally capable by the IMU sensor. Finally, these results act as more than a proof-of-concept because both the sensors are supposed to measure the same accelerations with the same operating frequency.

The primary reason for achieving this level of accuracy is due to feature extraction performed on the segmented data. The accelerometer and gyroscope measurements are collectively considered a group, and combined behavior is used to classify the user walking. This grouping of the sensor's measurements includes all the stance and swing phase parameters in walking. Hence, when all the sensor signals are combined, a unique characteristic is derived for the user with and without prosthesis walking. This unique characteristic is derived in the form of the decision tree from the Weka tool. When deployed on the IMU machine learning core, the generated decision tree from the tool can identify the unknown user walking into the category of symmetric or asymmetric walking. In addition, if data segmentation is done for more extended window sizes, more information is obtained to develop a unique characteristic to identify the walking. Because of this, more superior accuracy can be achieved. As we try to reduce the window size, the accuracy decreases because less information is obtainable to design a unique characteristic.

The straight forward analysis method focuses on a single parameter present in the stance phase (heel-strike) to determine the intermediate step duration. In contrast, in the machine learning method, all the parameters in walking are considered to generate a unique characteristic. This difference in parameter consideration has led to better results for the machine learning approach. Also, indicating there are specific parameters in walking which represent asymmetric walking. However, the disadvantage of this method is the criteria for asymmetry are visibly unseen, i.e., the exact difference or differences present in the walking are not presented. The derived criteria or unique characteristic is now more mathematically/logically represented in the form of a decision tree. But, in the straight forward analysis method, the criteria (intermediate step duration) can be identified/obtained and be practically seen. Overall, the machine learning approach suits for distinguishing the type of walking (symmetric or asymmetric) mathematically, but it comes with a trade-off where the criteria/unique characteristic differentiating the type of walking is not presented in a real-world context.

Chapter 6

Discussion

This chapter provides more insights and further discussions about the experiments conducted in this report. The future direction of work is also discussed for the same. Moreover, the discussion session is broken down into the following sections to address the sub-questions *(SQ)* for the main research question *(RQ- section 1.2)*:

6.1 - Gait abnormalities in hip/Knee prosthesis patients [SQ2]

6.2 - Identification of the gait patterns [SQ3]

6.3 - Wearability and feedback strategy[SQ4][SQ5]

6.1 Gait Abnormalities In Hip/Knee Prosthesis Patients

The results from the study for the users with and without prostheses have revealed the value of accelerations and velocities generated during walking. These measurements are tightly bounded to the location of the sensor, i.e., lower back. The results conclude a significant difference is unseen for the intermediate step duration for the users with and without prostheses. Identically, the same is observed for users with hip and knee prostheses. But, there are specific velocity patterns observed for the users with knee prosthesis, i.e., five out of six users have their pelvis rotated in the same direction for both feet heel-strike events. Moreover, the pelvis rotation is not in the same direction as the users with knee prostheses,i.e., in one user, the pelvis is rotated clockwise during both foot heel-strikes, and for another user, the pelvis rotated anti-clockwise for both foot heel-strike events. This pelvis rotation in one direction is unseen in the users with hip prostheses and without prostheses. This observation has provided potential criteria for addressing an asymmetry parameter in walking.

The initial intuition of intermediate step duration is different for the users with and without prosthesis was unbacked by the results from the study. The probable reason for this is none of the users with prostheses who participated in the study have not developed a pathological gait (for example, Trendelenburg gait, Steppage gait) after or before hip/knee surgery. However, the data collection from the study has demonstrated that the users with prostheses showed diverse walking patterns compared with the users without prostheses. This difference illustrates that other parameters in the walking activity are different, and there can be a potential criterion for defining asymmetry in walking among these parameters.

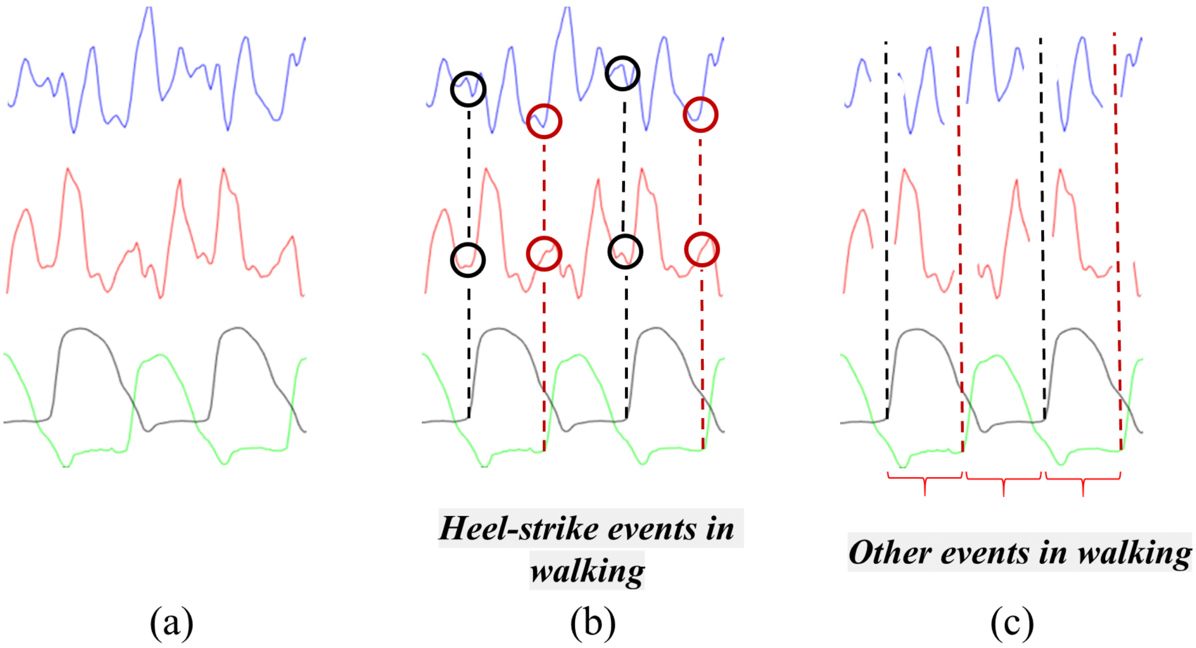


Figure 6.1: Measurements from gyroscope (top: blue - Y-axis, middle: red - Z-axis) and pressure sensor (bottom: black - right foot,green - left foot) for a user with prosthesis

Fig: 6.1(a) presents the gyroscope measurements along the Y-axis and Z-axis for a user with a prosthesis. The heel-strike event detected with the help of the pressure sensor is highlighted in black and brown circles in Fig: 6.1(b). The analysis presented in the study is focused on this particular region to determine the measurement values and intermediate step duration. However, there are other events that can occur between two heel-strikes, i.e., toe-strike,toe-off events in the stance phase, and other parameters in the swing phase. These signals for other events in walking are presented in Fig: 6.1(c). However, identifying other events in walking can be a challenging task because one IMU sensor is used to record the signals. This causes an overlap of events from both feet. Thus, identifying a particular event for an individual foot might be tricky, especially when considering real-time processing. But with the data collected in this report can be used for post-processing methods which can be developed to identify the other parameters in walking for future work. The level of understanding of the signals measured from the lower back position is magnified by performing this. Also, other potential differences in walking can be seen and probably able to derive better criteria to define asymmetry.

Apart from the sensor data to recognize the asymmetries in walking by the unhealthy patients, the visual observation of these subjects during walking resulted in an insightful observation that few participants tend to have different knee bending (moderate but noticeable amount). This bending is primarily seen during the swing phase of walking. However, the visible observation of this behavior in the sensor reading for this report can be challenging. With the sensor positioned on the lower back, there is already a huge complexity in identifying the other parameters present in the stance/swing phase. However, the sensor captured the subtle accelerations and velocities during the stance phase and swing phase. This resulted in various patterns in the measurements for the users with and without prostheses. But, with the naked eye, identification for the same is difficult. Eventually, these recordings only made it possible for the machine learning algorithm to distinguish the type of walking performed by the user.

6.2 Identification Of The Gait Patterns

The key focus of this study is performed on the heel-strike event. This event is selected because it is easily identified from the IMU sensor data and can be verified with the help of a pressure sensor in real-time rather than in post-processing. At the same time, the other events/parameters identification in real-time is a complex task. The majority of earlier research (chapter 2, section 2.2) focused on post-processing in determining these parameters. However, in this report, a parameter that can be easily determined in real-time is required. Hence, the heel-strike event was a starting point. Now, by using this event, the intermediate step duration is calculated. The hypothesis based on the intermediate step duration is formulated with the help of the head physiotherapist and literature reading (chapter 2, section 2.1). However, the intermediate step duration criteria to define asymmetry is not supported by the study results. The results have shown that users with and without prostheses have similar intermediate step duration values.

The development of the straight forward analysis method is discontinued due to the observation made from the study results. The implementation of this algorithm looked unproductive if the intermediate step-duration criteria could not distinguish the user walking. Moreover, a very recent (May 2021) publication by Apple Healthcare has used a Symmetry definition based on the swing and stance time as seen in equations 6.1, 6.2 [43].

$$symmetry = \frac{max(SSR_{left}, SSR_{right})}{min(SSR_{left}, SSR_{right})} \tag{6.1}$$

$$SSR = \frac{swing_{time}}{stance_{time}} * 100 \tag{6.2}$$

By using this symmetry ratio value from their definition, they categorized the walking performed by the user into three levels of symmetry (i) symmetrical gait if the ratio is between 1.0 to 1.1 (ii) mild asymmetry if the ratio is between 1.1 and 1.5 (iii) severe asymmetry if the ration is greater than 1.5. However, this data is collected in a fixed environment using a pressure mat to identify the swing and stance times. In addition, the users were asked to carry two iPhone devices- one on each side of the body- during this study. However, the data obtained from each phone is treated independently to develop the symmetry definition (equations 6.1, 6.2). Using a pressure mat presented a better opportunity to identify the IMU sensor patterns generated during the stance and swing phases of walking. In contrast, this is immensely complex to determine when using one pressure sensor inside the heel region of the shoe, which is done in this report. Because of the pressure sensor in the heel region, only the heel-strike event is detected. But to determine the time duration of stance and swing phase, detecting the toe-off event is also required. Therefore, for future work, an additional pressure sensor can be added in the toe region of the foot to identify the toe-off event. By doing this, a deeper understanding of the beginning and end of the stance phase can be observed for one sensor located on the lower back in real-time. As the stance phase is $\approx 60\%$ in one complete walking cycle, analyzing this entire phase may result in criteria for defining asymmetry in walking.

As the walking patterns recorded between consecutive heel-strike events looked different, which shifted the focus towards machine learning, knowing the advantages and capabilities of machine learning, this experiment was performed. The experiment was implemented to verify the patterns seen in the walking (symmetric and asymmetric) are different enough to distinguish by a real-time machine learning algorithm. Also, the challenge of real-time implementation for the same remains a concern. The classification of the user walking is not the intended result of this report, but the results of this experiment exist as groundwork for future implementations. By performing this experiment, the hardware suitable as a wearable device and compatible for executing a real-time machine learning algorithm is realized. In addition, it strengthened the observations made from diverse walking patterns recorded during the study, i.e., possible asymmetries present in different phases of walking for the users with prostheses.

Currently, the data used for this machine learning experiment is symmetric and asymmetric walking. However, for future work, more walking data needs to be collected and labeled accordingly. The collected data from the hip/knee prostheses users can be labeled according to the type of asymmetry. This type of asymmetry criterion needs to be identified by post-processing the collected data, and then labeling of the data should occur. After the labeled data are obtained by the asymmetry criteria derived from post-processing, a machine learning model can be developed and used in the wearable device to provide feedback accordingly. By giving the feedback, further studies can be performed to interpret the results of this feedback. The results for the same can give much deeper insight into the change of user walking patterns with the help of feedback. The latest hardware by Arduino (Arduino Nano Connect) made this idea feasible for a wearable device. This device is compact and powerful for running machine learning decision tree algorithms and implementing different feedback options (haptic, sound, etc.). A robust classification algorithm can be developed, and feedback can be provided for future work by utilizing this.

6.3 Wearability And Feedback Strategy

The usage of the IMU sensor and the location of this sensor on the human body (lower back) has provided effective results when using the machine learning method. This indicates that the lower back position is suitable for identifying the criteria for asymmetries generated during walking. However, the cause of these asymmetries is currently confined to the users undergone knee/surgery. Moreover, certain disadvantages are learned from the study when positioning the IMU on the lower back. As one sensor is used to measure the patterns generated by both legs, it introduces complexity in matching the patterns for the respective leg. Moreover, the patterns generated are always a combination of both leg motions.

The insights obtained from physiotherapists ensured in identifying routine feedback location on the user's body - hips and waist. Therefore, when feedback is provided to the user by a wearable device in those locations, the adaptation time required by the user can be reduced. Plus, the user may feel like they are resuming their training session from physiotherapy whenever they operate this device in their convenient places. Furthermore, from the literature readings, the haptic feedback and multi-modal feedback (haptic and sound) showcased a potential solution for this activity—however, various experiments needed to be done to understand these feedback options. Also, the intensity of feedback can be varied as per the user's rate of the development process. This varying feedback to the individual provides a custom experience and motivation to the user. The style/frequency of the feedback method can also affect the motivation of the users. Techniques like creating a gaming environment (challenges and targets) and statistics are designed to encourage users based on their progress. In general, these kinds of procedures are implemented for offline processing (after finishing the training session) applications to create motivation for the user. However, the exact implementation of these methods may not be suitable for this wearable device because the feedback to the user should be provided in real-time. Therefore, for future work, more user-based experiments might be required in developing an environment to motivate users to use the designed wearable device.

As the lower back location seemed to represent a possible location to detect the walking (symmetric or asymmetric), the feedback can additionally be provided at the lower back or both hips or either side of the hip. This can be an excellent starting point for the development process as this feedback location matches the physiotherapists' feedback location. Moreover, a similar waist belt (for IMU sensor) used for the users' data collection process can be utilized in further studies. The participants did not experience any discomfort using this device nor any intrusion into the walking activity. However, these observations cannot be legitimate as no feedback is collected regarding the design/construction of the waist belt. Hence, feedback regarding this waist belt is needed to finalize the design choices of the wearable device.

Chapter 7

Conclusions and Future Work

This chapter provides answers to each SQ designed to answer the RQ and future work for the same.

[SQ1] ***What is the state of art in wearables for motor learning using haptic feedback?***

The majority of earlier research mentioned in Chapter 2 relied on post-processing approaches to determine the walking gait parameters. Also, the wearables designed with sensors located in more than one location on the human body are majorly used for data collection for post-processing. Though they target to determine parameters in walking, the approach they opted for was post-processing. Indeed, there are researches with fixed setups (pressure mat, cameras, etc.) utilized to verify the derived parameters in post-processing. However, there are few activities where wearables are designed to process in real-time. They target to provide real-time feedback in assisting users to ensure they perform the proper movement or action. But, as per the literature findings collected for this report, there is no similarity with the use case (walking activity with hip/knee prosthesis) and methodology (real-time) considered for this report.

[SQ2] ***What gait abnormalities are characteristic for post hip/knee prosthesis patients?***

Walking consists of two phases (i) stance phase and (ii) swing phase. The combination of these two phases completes one cycle of walking. Standardly, the walking cycle is divided into 60% stance phase and 40% swing phase. In the stance phase, there are four key events (i) heel-strike, (ii) toe-strike, (iii) heel-off, and (iv) toe-off. These events help determine parameters of walking like step count, stride length, step duration, etc. All these parameters can be calculated for both legs. After the interview with the physiotherapist and literature reading, the following hypothesis is designed to characterize the walking of patients/users with hip/knee prosthesis: *The intermediate step duration differs a lot for the users with a prosthesis in the hip/leg, unlike the users without prosthesis.*

After performing a study with seven users without prostheses, six users with a prosthesis in the right knee, three users with a prosthesis in the left hip, and two users with a prosthesis in the right hip concluded that the intermediate step duration remained equal for all the participants. This observation negates the hypothesis. However, there are other observations from the study (i) the users consist of diverse walking patterns, especially the patterns generated by the pelvis movement (gyroscope measurements) caused by the hips motion connected to it, (ii) the users with prosthesis on the right knee have shown a pattern where their pelvis rotated in the same direction during both feet heel-strike events, and (iii) step duration for all the users are almost equal. All the observations obtained from the study are focused on the sensor measurements obtained during the heel-strike event. This is chosen so that the criteria obtained will be helpful in real-time processing to distinguish the type of walking performed by the user.

[**SQ3**] ***How to identify the relevant gait pattern?***

The gait pattern identification is developed in two approaches (i) straight forward analysis method and (ii) the machine learning method. The straight forward analysis method represents a traditional approach of developing a real-time algorithm where single or multiple criteria are used to decide the outcome of the algorithm. For this report, the hypothesis is used as the criteria for deciding the type of walking performed by the user. To execute this, exponential weighted moving average (EWMA) filter, findpeaks function from MATLAB, and data segmentation methods are used in calculating the intermediate step duration. However, this algorithm is unverified with users, and robustness checks are undone due to the results obtained from the study performed with users.

Instead of investing time on straight forward analysis method for further development, the focus is shifted towards machine learning. This is performed because there are different walking patterns generated for the users with and without prostheses. Hence, the latest hardware capable of deploying machine learning in real-time and meeting this report's wearability requirements is realized. The Arduino Nano has demonstrated the potential to run a classification model in real-time to distinguish the type of walking. This report uses a binary classification model with the variance as the feature attraction method, and a decision tree is derived (REPTree). This classification model is trained with the user's data obtained from the study. The obtained data are divided into two labels (i) symmetric walking data and (ii) asymmetric walking data. The classification model has shown a 96.96% accuracy. However, this classification model is unverified with any external user, but the outcome from the model has indicated the potential of being effective in identifying the type of walking (symmetric/asymmetric) in real-time. The classification of the user walking is not the intended outcome of this research, but the findings serve as a foundation for future implementations.

[SQ4] ***What contributes to wearability for a haptic feedback system?***

The device constructed in the second development represents a base design for a wearable design for this report. This design consists of a waist belt that holds the necessary components in the lower back location, is comfortable for the user during the walking activity, and is non-intrusive in the user's activity. The waist belt is designed with a soft fabric material that does not cause any discomfort for the user and is durable to contain the components. The device supports the necessary components in a secure position on the lower back throughout the walking activity without any shift in position. This is achieved with the help of the adjustable bands attached to this device. The user can adjust them according to their comfort and ensure the proper position of the sensor. Moreover, the sensor's signals have exhibited good results in capturing the events occurring during walking activity for both the users with and without prostheses. These patterns have provided encouraging results when using the machine learning method. This lower back position or adjacent position (hips) can be utilized in giving feedback to the user. This location of feedback matches with the physiotherapists' feedback location. As the user is already habituated to obtaining feedback in that location, this makes it an ideal beginning point to provide feedback.

[SQ5] ***What is effective and "simple" haptic feedback for gait training (in our case)?***

By the end of this thesis, there are suggestions for this question, but no answers. A sure criterion is not derived to address the asymmetry to finalize the necessary algorithm and device. All the efforts have been invested in obtaining this criterion for defining the asymmetry. However, the study results are not in favor of proceeding further in the design process of a wearable device that provides feedback for the user. However, a few related sports requiring lower limb movements, such as running and rock climbing, can be used as a starting point for exploration because these sports employ haptics to provide concurrent feedback to the users.

Overall, all the above answers to the SQ have resulted in answering the RQ partially. The main functionality of this wearable device is to identify and distinguish the asymmetry present in walking, which was partially answered in this report with the help of machine learning. The traditional method of using single or multiple criteria does need more work to identify the relevant criterion to determine asymmetry in walking caused by the users with hip/knee prostheses. The analysis performed for the heel-strike event could not provide strong criteria for defining asymmetry. Additionally, it has led to a result that is against the hypothesis. However, the real-time machine learning method has presented promising results to adapt it for future implementations. But, the criteria derived from this approach are logically available in the form of a decision tree. This interpretation might not be genuinely helpful in understanding the asymmetry, but it can identify similar asymmetry in any user walking. Now providing feedback to the user to overcome this asymmetry is not performed in this thesis because this is the later stage of designing a wearable. However, the designed waist belt and the lower back location on the human body have the ability for being the right wearable design and location to provide feedback to the user to assist in motor re-learning.

7.1 Future Work

To determine criteria for defining the asymmetry in walking for users with the hip/knee prosthesis by the following ideas can be a perfect starting point:

(i) Identification of the toe-off event in walking and analyzing the sensor measurements for that event. By performing this, there is a possibility that new criteria can be developed based on the symmetry defined by Apple Healthcare [43]. Because SSR defined by them can be obtained in real-time by identifying the toe-off event. In addition, this SSR itself can act as a criterion for defining asymmetry. However, more study is required to confirm this.

(ii) As the IMU sensors are small, more of them can be integrated onto the waist belt designed in this report. The additional sensors can be positioned on the left and right sides of the hip. This can result in deriving more information of walking events of each leg more explicitly. Over time, an algorithm using these three sensors (lower back, left hip, and right hip) information can be developed.

(iii) Performing a post-processing work on the data collected from the study conducted in this report. This can assist in perceiving more intermediate events in walking for the users with or without prostheses.

(iv) Development of better machine learning classifier by exploring the TinyML software. Because the capabilities of deploying more advanced machine learning models are possible through this rather than the dedicated machine learning core (decision trees) in the IMU present on the Arduino Nano. However, the window size can remain a challenging aspect to ensure accuracy.

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Appendix A

Data Collection Procedure

File Creation In Micro SD Card:

The file creation happens in the following manner:

- Whenever a battery is connected the file creation begins from start. i.e. for every power cycle of the device, the file creation always happens Run10.txt, Run11.txt, Run12.txt, ... etc (file is created when the button is pressed)
- For every user, it repeats the same file names for a power cycle. Therefore, the files from Micro SD card should be copied into a PC and deleted from the Micro SD card after user is finished with the data recordings. By doing this it prevents the overwriting/appending to the existing files for different users

Pre-Check Conditions:

- Battery is connected
- Micro SD card is inserted
- Device is located at the lower back position
- Pressure sensors are positioned inside the shoes
*(**Note:** Ensure there is no shorting of wires and has enough length to not disturb the users waking)*

Post Check Conditions:

- Remove the Micro SD card
- Copy the files into computer and delete those files from the SD card
*(**Note:** Files should be deleted from SD card to ensure no overwriting of new data into the existing files)*

LED Colours:

 : (No light) No data recording is performed

 : (Yellow) Initiating data recording

 : (Green) Data is recording

 : (Red) Finishing data recording

LED Colour Transitions:

 This transition should occur when the user presses the button to ***start recording data***

 This transition should occur when the user presses the button to ***stop recording data***

Appendix B

Experiment Forms

B.1 Brochure

Dear reader,

In this letter, we would like to inform you about the research you have applied to participate in. The experiment will take place on . . . ., in room . . . . of the Ambulantes Physiocenter Gronau GmbH, Germany. In the proposed research, entitled "***Wearable Coach For Symmetric Walking***", we will record the accelerations caused by different walking patterns of human - that undergone knee/hip surgery. The data collected from this study can be used in further research towards designing a wearable device to assist humans to walk symmetric.

During the study, you will be requested to wear a small pouch around your waist (with adjustable bands) and pressure sensors inside your shoe. The pouch will be positioned to lower back side. An instruction manual is also provided to you before the experiment. This manual illustrates how to wear, use and position the device according to the experiment setup. Your task is to wear this device as recommended and walk in a straight line for 40s to 60s.

After wearing the device, you can free yourself at any time by releasing the clamp attached to the bands. You can decide to stop at any point in the course of the experiment without this having any consequences for yourself and without giving any reasons. In addition, you can still decide at the end of the experiment and any time after the end of the experiment, that your data may not be included in the research after all. Other relevant aspects are that your data will be handled in a confidential manner, the anonymity of your data is guaranteed and will never be disclosed to third parties without your permission in the consent from.

The experiment lasts for a maximum of $20min$–$30min$, but there will be breaks in between. After the experiment, you will receive a debriefing. At the end of the entire research, you may, if you so wish, be informed about the results obtained by means of a debriefing.

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B.2 Consent

Research: ***Wearable Coach For Symmetric Walking***

This research is by the University of Twente in the context of a M.Sc. thesis for Embedded Systems. The supervisors work in the HMI department.

Main researcher: *Sai Kishan Rali* (s.k.rali@student.utwente.nl)

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The aim of this study is to collect data on human-that undergone knee/hip surgery-walking patterns. The data collected by this experiment will be used to observe patterns generated while walking. This data collection helps in further research of designing a wearable device to assist humans to walk symmetric. This research will be carried out by the Human Media Interaction (HMI) group of the University of Twente as part of my Master Thesis.

During the study, you will be requested to wear a small pouch around your waist (with adjustable bands) and pressure sensors inside your shoe. The pouch will be positioned to lower back side. Your task is to wear this device as recommended and walk in a straight line for 40s to 60s. The device is light in weight and purely meant to ***record***

the accelerations caused while you are walking. Hence, there is ***no feedback*** (sound, vibration) provided to you. However, you can stop walking and remove the device at any time.

Participation is voluntary. The data will be safely stored and processed according to AVG guidelines. You can withdraw at any time, without giving a reason. Your data will in that case be deleted.

The data will be analysed for research purposes. The analysis will be published in the M.Sc. thesis. The results presented in any publications are fully anonymous. If you change your mind later and you want your data to be removed, you can contact me.

Declaration of Consent (Please tick each checkbox if you consent)

o I agree to participate in this study
o That I'm fully informed about the research. The goal of the research and the method are clear, any questions I had after reading the explanatory text were answered.
o I understand that I can withdraw from the research, without giving a reason, at any time without consequence.
o I give permission for collecting and using the data as described above.

Name Participant

Signature Participant

Appendix C

Codes

All the necessary codes used/created for this thesis are provided in the following GitHub repository:

https://github.com/SaiKishanRali/Code