

Development of Hybrid Ankle-Foot Prosthesis

Thesis

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**ELECTRICAL AND INSTRUMENTATION ENGINEERING
DEPARTMENT**

by

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Dedicated to my father

Late Udai Narain Gupta

CERTIFICATE

I, hereby declare the work presented in the thesis entitled **Development of Hybrid Ankle-Foot Prosthesis**, in partial fulfillment of the requirements for the award of the degree of **Doctor of Philosophy** and submitted to the Electrical and Instrumentation Engineering Department, Thapar Institute of Engineering & Technology, Patiala, Punjab, is an authentic record of my own work carried out under the supervision of **Dr. Ravinder Agarwal**.

The matter presented in this thesis has not been submitted elsewhere for the award of any other degree in India or Abroad.

Date: 30/07/2020



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This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

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Achievement of the goal is feasible with strong determination and guidance. The only way to success and knowledge is constant efforts with zeal and passion. In this journey, nature plays its role by providing sources and limelight to show the right way. I would like to thank those persons who helped me to achieve my goals.

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SUMMARY

Limb loss of humans produces a permanent disability that impacts the amputee's self-confidence, self-care, and limb movement. Specifically, lower limb loss results in slow and less stable locomotion. Below-knee (transtibial) amputation is one of the most frequent types of amputation around the world. The ankle-foot prosthesis is one of the solutions meant to provide support and assistance to the transtibial amputee. The majority of available ankle-foot prostheses are passive and not able to provide required push-off and seamless movement during locomotion. However, active ankle-foot prostheses can provide desired characteristics and seamless operation to achieve by embedding subject locomotion intention in the control sequence of the prosthesis. EMG signal is a well-reorganized way of capturing neural information of human limb movements to identify the locomotion intention of the subject. The prime objective of the present research work was to develop a hybrid ankle-foot prosthesis prototype.

Here, the EMG signal of six lower limb below-knee muscles for non-weight bearing and weight-bearing dorsiflexion/plantarflexion ankle-foot movements had been analyzed. Tibialis Anterior and Gastrocnemius muscles had been found suitable for repetitive ankle-foot movements. Further, to incorporate subject locomotion intention in the control sequence of the prosthesis, hybrid information (EMG+knee joint angle) based activity and locomotion prediction module had been designed. It had a two-level classification approach, the first level of classification predicts the activity (*standing or walking*) of the subject, whereas the second level predicts the locomotion (*level walking, stair ascent, stair descent, ramp ascent, and ramp descent*) intention of the subject only if at level-1 walking activity had been identified. EMG signal of four lower limb muscles (*Tibialis Anterior, Gastrocnemius, Vastus Lateralis, and Biceps Femoris*) with knee joint angle signal were used in both levels of classification. A continuous windowing technique with window size 256 msec and window shift 32 msec had been applied at level-1 classification to monitor subject activity continuously. Whereas for level-2 classification, four subwindows, each of size 200 msec, had been extracted over the complete gait cycle, and an individual classifier was trained for each subwindow. The performance of three classifiers (LDA, SVM, and NN) had been compared for both levels of classification. The performance of the LDA classifier had been found better as compared to other classifiers for both levels of classification.

After that, an ankle joint angle estimation module had been developed using the Non-negative Autoregressive Exogenous model as a training algorithm. The angle estimation module served as a low-level controller for the prosthesis and estimate ankle-foot angular position continuously using the EMG signal of two lower limb below-knee muscles (*Tibialis Anterior*, and *Gastrocnemius muscles*) and knee joint angle signal. An individual model had been designed for each locomotion. The performance of the estimation model had been found satisfactory for each locomotion, which justifies its applicability for ankle-foot prosthesis control. Moreover, the knee joint angle signal information had been found very useful, and its incorporation with EMG signal resulted in significant improvement in model performance. Finally, an electric actuator operated an ankle-foot prosthesis prototype, with one-DoF and dorsiflexion/plantarflexion movement had been developed. The estimated ankle joint angle was used to generate a control signal to operate the developed prototype in offline mode.

LIST OF ABBREVIATIONS

%	Percentage
Ccoef	Correlation Coefficient
CPG	Central Pattern Generation
DBNN	Dynamic Bayesian Neural Network
DF	Dorsiflexion
DRNN	Dynamic Recurrent Neural Network
DT	Decision Tree
EMG	Electromyogram
FSR	Force Sensitive Resistance
FWHM	Full Width at Half Maximum
HS	Heel-Strike
IMU	Inertial Measurement Unit
KA	Knee-joint Angle
LDA	Linear Discriminant Analysis
LOOCV	Leave One Out Cross Validation
MF	Median Frequency
MUAP	Motor Unit Action Potential
NB	Naïve Bayes
NN	Neural Network
PF	Plantarflexion
RMS	Root Mean Square
RMSE	Root Mean Square Error
RoM	Range of Motion
SVM	Support Vector Machine
TO	Toe-Off
WAH	Window After Heel-Strike
WAT	Window After Toe-Off
WBH	Window Before Heel-Strike
WBT	Window Before Toe-Off

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Chapter 1

Introduction

“All the technological advancements are meant for mankind.” *The scientific innovations are interrelated to the society and vice versa. An able human can take steps for a walk without any cognitive effort, whereas similar actions by a lower limb amputee are not such an easy task, both physically and mentally. Human intellect has always been endeavoring to invent artificial limbs for amputees since almost the beginning of civilization. However, a fully functional artificial limb replacement having all the essential human attributes is still far from realization. With the advent of modern robotics technology and actuation principles, new features for prosthetic devices are being achieved through biomimicry of muscular actuation systems.*

1.1 Amputation and Prosthesis

Amputation is an acquired condition that results in the loss of a limb partially or entirely. It can occur due to accidents, animal attacks, or battles, *etc.* It is also performed as a surgical procedure. In the USA, it is estimated that 185,000 persons undergo amputation of the upper and lower limb each year [1]. Figure 1.1 shows the different types of amputations with their respective frequencies. The most frequent type of amputation is the below-knee amputation (*transtibial*) followed by above-knee amputation (*transfemoral*) [2,3].

Figure 1.2 depicts the causes of amputation with their relative percentages. Peripheral arterial disease and diabetes are the most common reason for lower limb amputation [4]. Trauma is the second major cause of amputation around the world. The number of people whose amputation is due to trauma varies from country to country. In developed countries, trauma usually occurs as a result of industrial accidents, farming accidents, or motor vehicle accidents, which include automobiles, and train accidents. Trauma accounts for approximately 9-10% of new amputations. In countries with a recent history of war or civil unrest, trauma can account for up to 50% or more of all amputations. United Nations Organization statistical data indicates that mines kill or disable over 150 people each week. Such incidents often include losses like multiple limbs, chest, genitals, and the face. Congenital malformation accounts for a small portion of reported amputations [4,5].

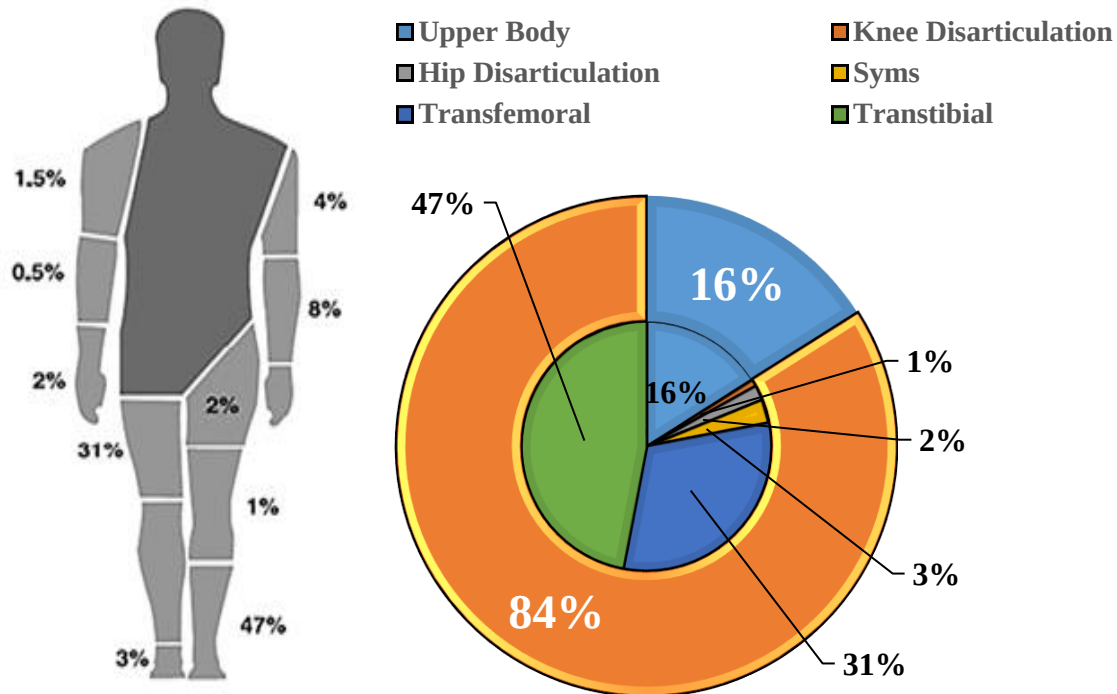


Figure 1.1 Different levels of amputation with their respective frequency of occurrence

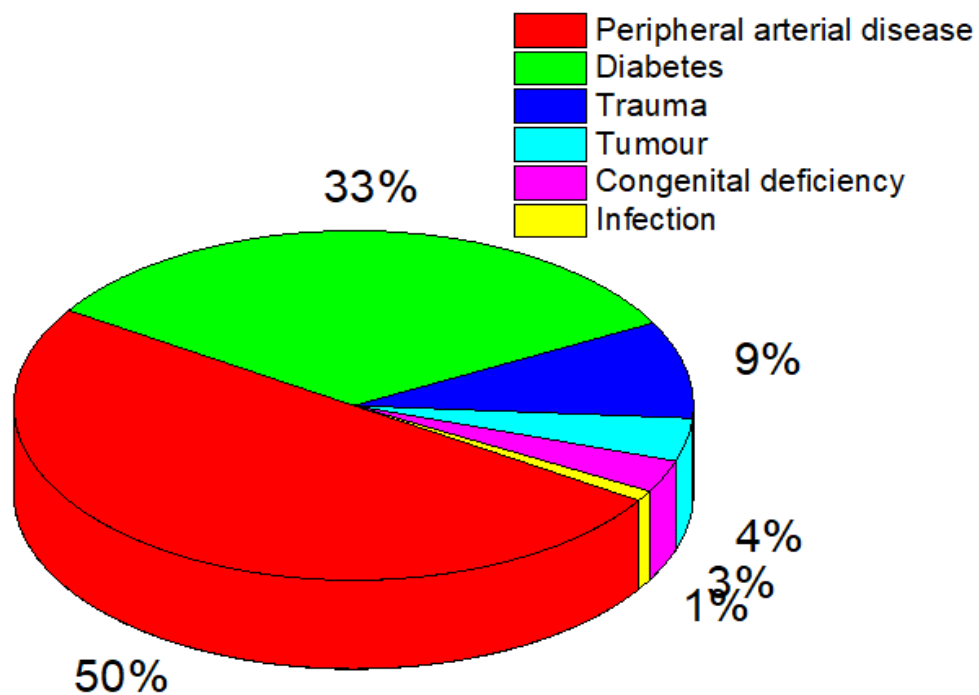


Figure 1.2 Causes of lower limb amputation with their relative percentages

Lower limb loss is a potentially disabling condition affecting the health and well-being of the person worldwide. Table 1.1 shows the increase in metabolic energy of amputee persons, as compared to a healthy human subject, required for a regular walk for different amputation levels [6]. The person living with transtibial limb loss face distinct challenges; they need more metabolic energy and cognitive effort to perform any locomotion related task. Moreover, their locomotion is very slow and unstable. Innovations in the design and development of new prosthetic devices should address these clinical issues [7].

Table 1.1 Additional metabolic energy required for walking with leg amputations

Level of Amputation	Addition Required Energy
Partial Foot	10-20%
Symes	0-30%
Below-knee	40-50%
Above-knee	90-100%
Bilateral Below-knee	60-100%

The lower limb prosthesis is considered as the substitute for the lost limb of an amputee. The rapidly increasing figures of amputation around the world always motivate the researchers to provide its effective solution as efficient prosthesis. The development of lower limb prosthesis has a vast history [8]. The initially developed prostheses were completely passive and provided only support to the lower limb. Most of the time, the passive prosthesis is augmented with passive elastic elements, which stores and releases energy in different phases of the gait cycle. These passive elements underperform as compared to the biological limb (such as ankle here) in producing required push-off during locomotion. However, active prostheses can provide the required push-off. However, such powered prostheses required adaptability and an indispensable controller. In these prostheses, the control commands for cyclic/rhythmic activities are synthesized via Central Pattern Generators (CPG) with the locomotion model of humans. Control command generation using Electromyogram (EMG) signals offers a viable technique for prosthetic actuation and control. A blend of CPG and EMG signals provide an effective solution in controlling a device like ankle-foot prosthesis [9].

1.2 Human Lower Limb Anatomy and Gait Cycle

This section covers the basics of human lower limb anatomy and gait cycle in brief. The lower limb anatomy includes ankle as well as knee movements and their responsible muscles. The human gait cycle covers its definition, description during walking, and biomechanical characteristics.

1.2.1 Ankle-Foot Anatomy

Human ankle-foot is designed to provide a stable platform so that the dynamic activities of daily life can be performed. It provides contact between the human body and the environment during various activities like sitting, standing, walking, and running. It must be able to provide the required Range of Motion (RoM), control, and stability to the body during various activities. The ankle-foot work act as a shock absorber and weight bearer. Figure 1.3 shows the major bones, joints, and ligaments of human ankle-foot [10]. The ankle-foot is a complex skeletal structure having 33 joints, 28 bones, and 112 ligaments.

The complex structure of ankle-foot is controlled by 20 intrinsic and 11 extrinsic muscles. The complete entity of ankle-foot is rigid enough to bear bodyweight, and at the same time, it is also flexible in dealing with uneven terrains [11]. The ankle joint is made up of mainly three bones, namely; Tibia, Talus, and Fibula. Whereas, the complete foot can be divided into three subparts as rear-foot (tarsus), mid-foot (metatarsals) and fore-foot (phalanges). Calcaneus is considered as the biggest bone in the foot and resides in the rear foot part. It transmits the load from the body to the ground and serves as a moment arm for the calf muscles to generate sufficient moment for propulsion to move the body forward. The talus bone is attached to the calcaneus bone of the foot (heel bone) through Achilles tendon and provides articulation at the subtalar joint [11]. The RoM of ankle-foot is defined around the particular joint in any DoF. The ankle-foot has three-DoF, one in the sagittal plane, one in the transverse plane, and one in the frontal plane. Hence, there are three possible motions of human ankle joints; dorsiflexion (DF)/plantarflexion (PF), inversion/eversion, and abduction/adduction. Table 1.2 shows the RoM of ankle joint motions along with their respective reference planes [12].

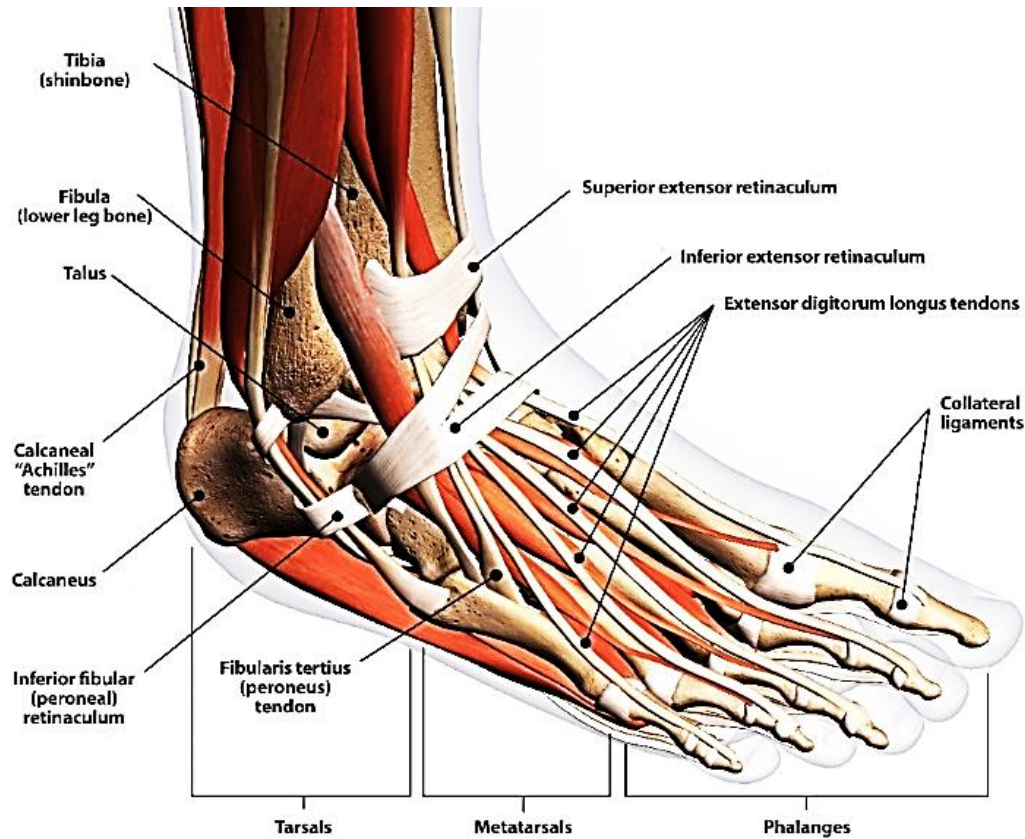


Figure 1.3 Ankle-foot bones, joints, and ligaments

Table 1.2 RoM of a natural human ankle

Motion	RoM (Degrees)	Reference Plane
Dorsiflexion/Plantarflexion	20/50	Sagittal
Inversion/Eversion	35/25	Transverse
Abduction/Adduction	20/25	Frontal

Figure 1.4 shows the different movements of the ankle-foot [13]. The movement of the ankle joint, pointing the foot towards the leg, or movement of toes lifting the foot away from the sole, termed as DF. The movement at the ankle joint, pointing the foot downwards away from the leg or movement of the toes that curl them down towards the sole, is termed as PF, shown in Figure 1.4(a). At the ankle joint, inversion is the movement of turning the sole inwards, and eversion is the movement of turning the sole outwards, as shown in Figure 1.4(b). Abduction and adduction movements are in the frontal plane and involve moving the body part away or towards an

imaginary center line. Abduction is taking the body part away from the central line, and adduction is moving it towards the central line, as shown in Figure 1.4(c).

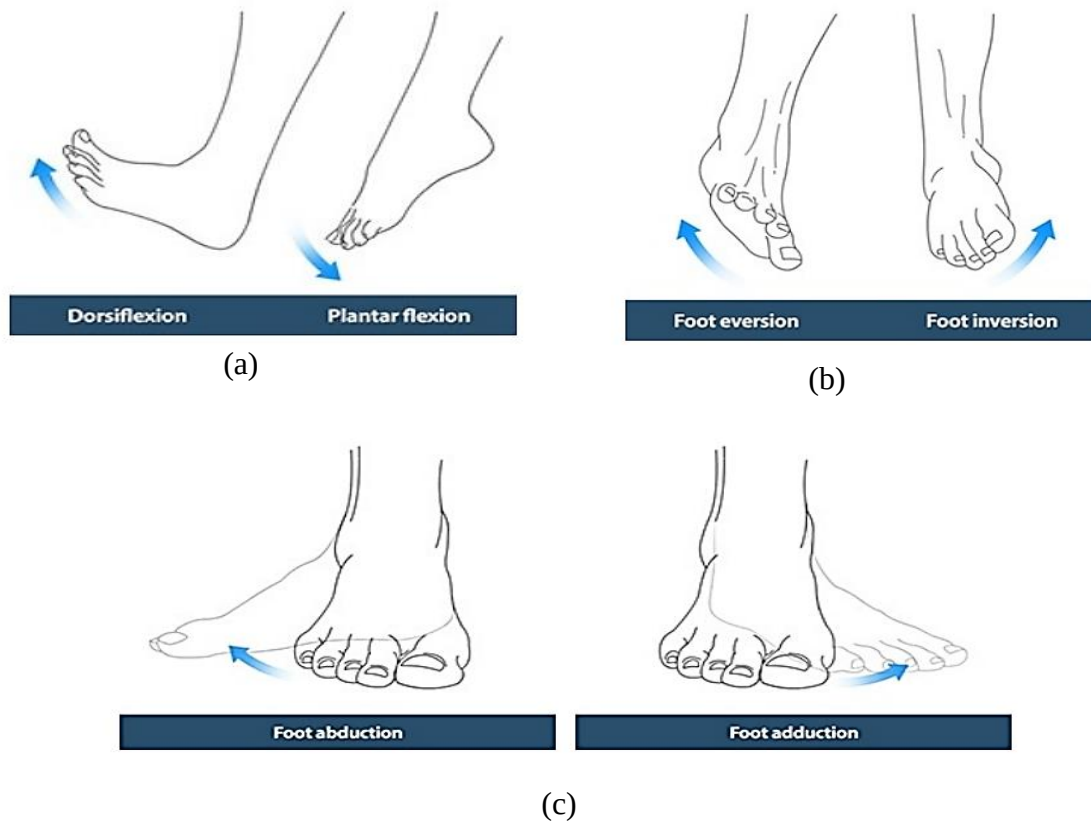


Figure 1.4 Human ankle-foot movements

Various lower limb muscles control the movements of the ankle-foot structure. The musculature of the ankle and foot classified into two parts, intrinsic and extrinsic muscles. There are 20 intrinsic layered muscles in human foot support locomotion by extending, flexing, abducting and adducting the toes and the arch of the foot whereas 12 extrinsic muscles or longer muscles are spanning tibia and foot act as the main drivers for ankle major joint motions. These muscles are; Gastrocnemius (Gast), Soleus (Sole), Tibialis Anterior (TiAn), Tibialis Posterior (TiPo), Plantaris (Plan), Peroneus Brevis (PeBr), Peroneus Longus (PeLo), Peroneus Tertius (PeTe), Flexor Digitorum Longus (FIDL), Extensor Digitorum Longus (ExDL), Extensor Hallucis Longus (ExHL) and Flexor Hallucis Longus (FeHL). Figure 1.5 shows the anatomical illustration of major below-knee muscles [14].

The ankle joint is very complex and provide motion about two axes. Muscles contraction associated with ankle joint motion about a particular axis is defined as primary muscle actuators. However, it is sporadic that a muscle contraction results in only a single axis of rotation, generally a secondary joint of motion transpires as a byproduct. Thus, each rotational axis has primary as well as secondary muscle actuators, as summarized in Table 1.3 [14].

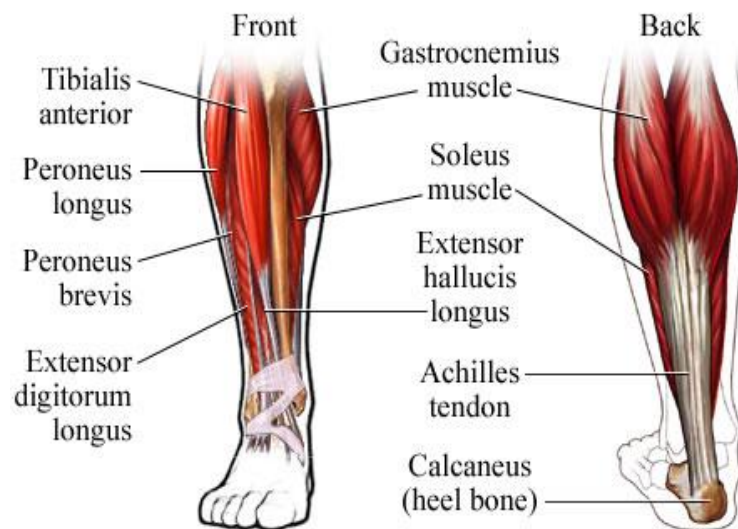


Figure 1.5 Major below-knee muscles of the human

Table 1.3 Primary and secondary movers for each axis of motion of ankle joint

Joint Movement	Primary muscle actuators	Secondary muscle actuators
Dorsiflexion	TiAn	ExDL, ExHL, PeTe, Plan
Plantarflexion	Gast, Sole	TiPo, Plan, FIDL, FIHL, PeBr, PeLo
Inversion	TiPo	FIDL, FIHL, TiAn, ExHL
Eversion	PeBr, PeLo	PeTe, ExDL, ExHL

1.2.2 Human Knee Anatomy

The knee joint is made up of bones, muscles, cartilage, tendons, and ligaments. The bones provide essential support and a rigid structure to the knee joint. The ligaments offer stability and muscles helps in the joint movement. There are four bones in the human knee joint, namely; femur, tibia, fibula, and patella. These bones are also referred to as the thigh bone, the shin bone, the smaller bone running alongside the tibia, and the kneecap, respectively. Figure 1.6 shows the lateral as

well as the anterior view of the knee joint [15]. The two joints of the knee, Tibiofemoral (between tibia and femur) and Patellofemoral (between patella and femur), work together and forms a modified joint that allows the knee to extend and rotate slightly (side to side).

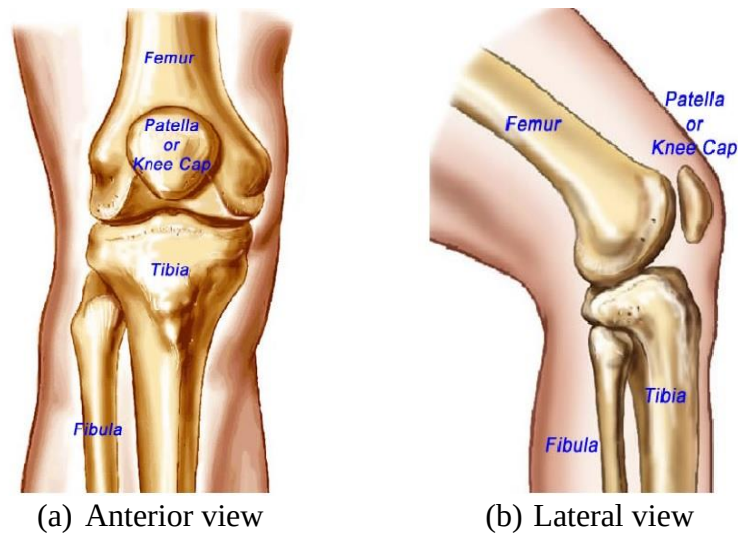


Figure 1.6 Human knee joint

The primary movements of the knee joint are flexion and extension about the virtual transverse axis in the sagittal plane. When flexed, the knee can be rotated slightly medially and laterally. Knee flexion is the movement of the shank towards the thigh, thereby decreasing the knee joint angle (KA). This knee movement is attained by the contraction of the knee flexor muscles. Knee extension is a straightening of the knee that is the movement of shank away from the back of the thigh, and it is achieved by contraction of knee extensor and relaxation of knee flexor muscles. Figure 1.7 depicts the knee movements [16].

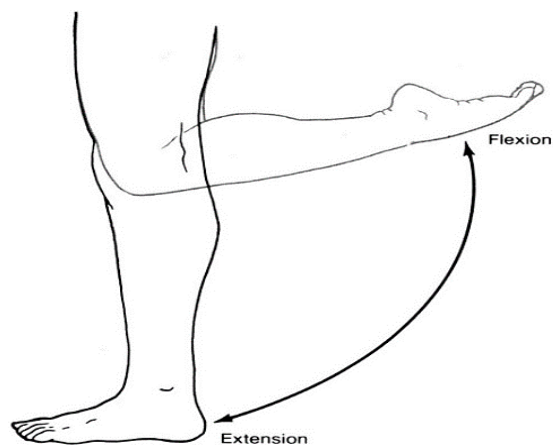


Figure 1.7 Human knee joint movements

Muscles responsible for knee joint movements are divided into two categories; knee flexors and knee extensors. Knee flexors consist of muscles, which are responsible for knee flexion. The knee flexors showed in Figure 1.8(a), are a group of seven muscles which cross the posterior of the knee joint (except the sartorius muscle). Knee flexors comprise of the hamstrings (Biceps Femoris (BiFe), Semimembranosus (Semb), and Semitendinosus (Semd)), the gastrocnemius muscle, the gracilis muscle, the sartorius muscle and the popliteus [17]. The knee extensors are a group of five muscles located towards the anterior thigh. Their contraction induces the extension of the knee joint by pulling the calf and foot back to their anatomical position. During this motion, knee flexors are relaxed, returning to their normal position. Knee extensors showed in Figure 1.8(b) comprises of the tensor fasciae latae and the quadriceps (Rectus Femoris (ReFe), Vastus Lateralis (VaLa), Vastus Intermedius (VaIn) and Vastus Medialis (VaMe)) [18].

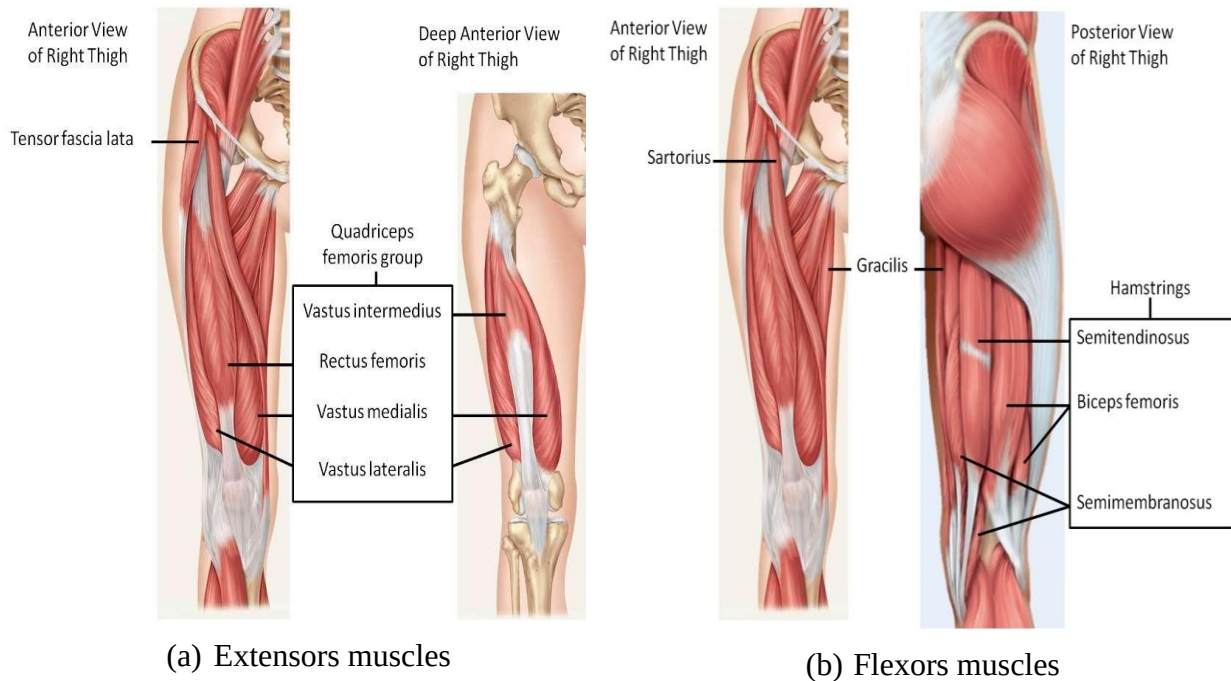


Figure 1.8 Major muscles of the human knee

1.2.3 Human Gait Cycle

Walking is one of the important and essential parts of human activities. It is illustrated as a gait cycle and has a cyclic sequence of foot movements to move the body forward. A typical human gait cycle consists of two phases, namely, stance phase (when the foot is on the ground) and swing phase (when the foot is in the air). Usually, the stance phase is 55-60% of the complete gait cycle,

and the swing phase is 40-45% of the complete gait cycle. Figure 1.9 depicts a human gait cycle for level walking with different phases and sub-phases.

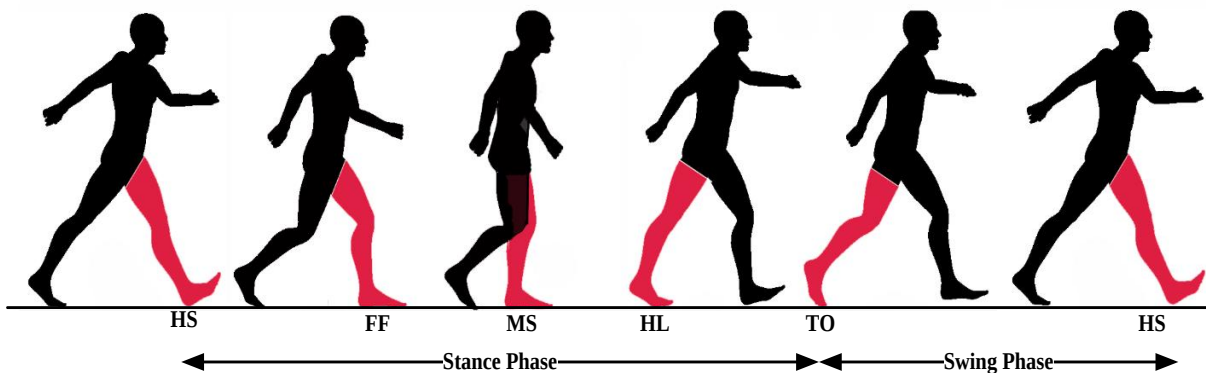


Figure 1.9 Human gait cycle for a level walk

The stance phase initiated with the Heel-Strike (HS) of the leading foot on the ground while the trailing foot is still in contact with the ground. At this time, the body weight starts transferring to the leading foot. After that, Flat-Foot (FF) sub-phase started in which the leading foot comes in full contact of the ground, and the total weight is shifted to the leading foot. This sub-phase ends when the entire human body is supported by leading foot, and the trailing foot is about to leave the contact with the ground. The Mid-Stance (MS) sub-phase starts, which ends when the opposite foot aligns with the stance foot. It is also considered as the mid-sub-phase of the stance phase and occurs during the 25-30% of the complete gait cycle. After that, the Heel-Off (HO) sub-phase starts, which terminates with the Toe-Off (TO) of the same foot or at the start of the swing phase. During the swing phase, the foot is in the air, and the new gait cycle of the same foot starts when the HS event for the same foot occurred again [19]. During the different phases of the gait cycle, the ankle joint modulates its stiffness and angular position to provide sufficient propulsion force. This ankle joint angular position modulation ability helps humans to walk on different terrains (level, stair, and ramp). During level walking, the human ankle joint angle follows a specific profile, also known as displacement profile. Figure 1.10 shows the normalized displacement profile during a complete gait cycle with the phases and events of the gait [20].

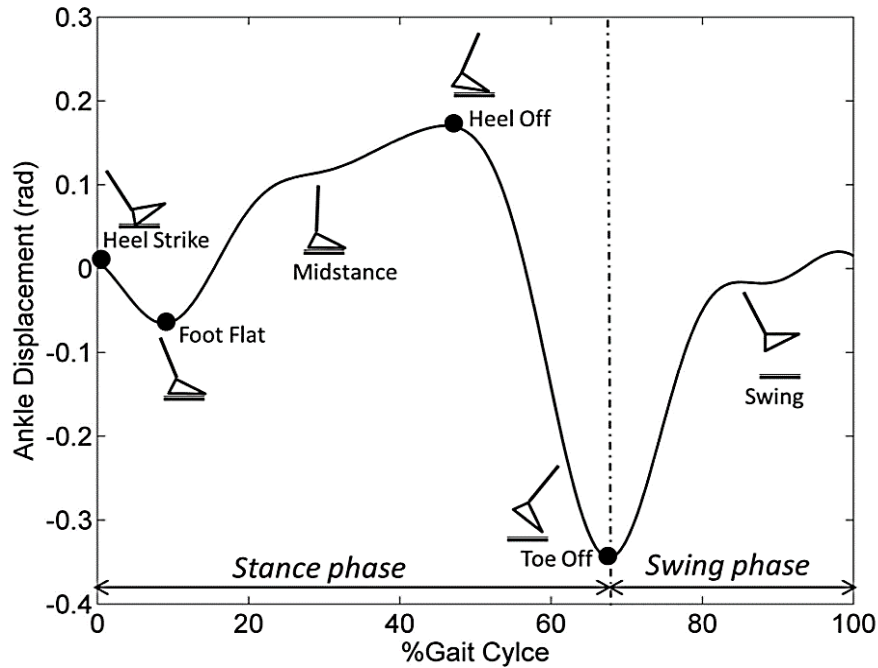


Figure 1.10 Gait cycle with ankle joint angle during the level walk

1.3 EMG Signal

Myoelectric signal manifests due to neural commands issued over the peripheral nervous system to activate human limb muscles. It is produced as an electrical impulse and subsequently generates muscle fibers contraction in the human body. This electric impulse is mostly used about skeletal muscles to controls limb movements. A skeletal muscle is made up of several fiber cells of various length (few mm to 30 cm) and diameters (10 μm to 100 μm). Every muscle fiber contains myofibrils having a dense array of protein filaments. Motor neurons carried the neural message from the brain to protein filaments and result in muscle contraction. Usually, during muscle contraction, its length is reduced by 50% of its resting length. This muscle contraction is of three types; isometric, concentric, and eccentric. In isometric contraction, the muscle length remained unchanged during muscle contraction. The isometric contraction usually occurs during posture control. In concentric and eccentric contraction, the length of muscle shortens and increases respectively [21].

A motor unit is formed with the motor neuron, axon, and muscle fibers, shown in Figure 1.11. It gets activated only when the brain decides limb movement, *e.g.*, to move the leg, the nerve impulse stimulates the contraction, carried in the nerve through motor neurons from the brain to muscle. It

divides into many branches (axon terminals) as motor neuron reaches near the muscle. Individual muscle fiber in a motor unit is connected to the respective axon branch to the accompanying motor neuron at a junction, known as the neuromuscular junction. It is mostly localized at the center of the muscle length and named as the innervation region.

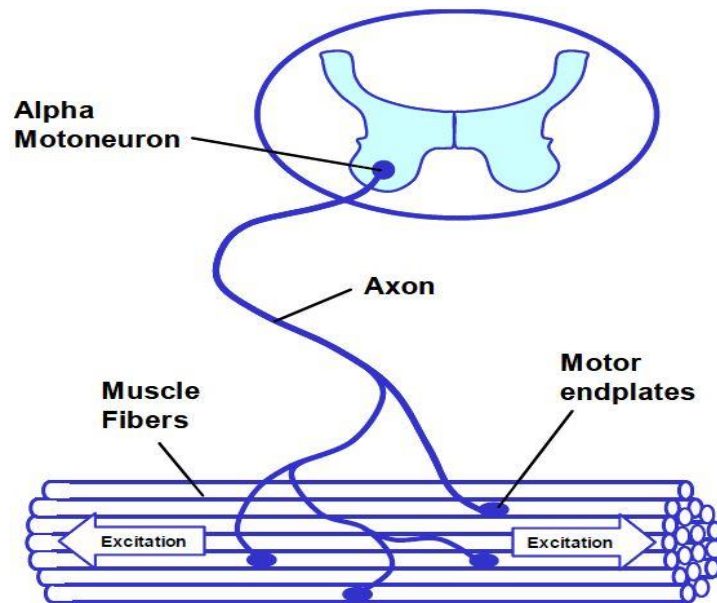


Figure 1.11 Motor unit illustration

Motor Unit Action Potential (MUAP) is defined as a resultant action potential of individual muscle fiber within the motor unit. The shape and duration of the MUAP imitate the architecture of the motor unit. Its amplitude is directly proportional to the radius of the muscle and carried inverse relation with the distance between active fiber and the pickup site. This signal is also known as the EMG signal. The amplitude of the EMG signal is quite random and can be represented as a Gaussian curve. It ranges between a few μV to $100 \mu\text{V}$ depending on the muscle under observation. It carries frequency components of 1 Hz to 10 kHz frequency range along with dominant signal power between 20-300 Hz. EMG signals are primarily studied for two applications, namely clinical and kinesiological [21]. Physicians, neurologists, and physiatrists do clinical studies by observing the characteristics of the MUAP to diagnose neuromuscular diseases and injuries. Kinesiological EMG is used for limb movement studies. It is utilized by the physical therapists and ergonomists to determine the behavior of the muscles during the limb movements of the subject. In particular, application surface EMG (sEMG) is preferred due to its non-invasive nature.

1.4 Objectives

The prime objective of this work is to develop a prototype of an ankle-foot prosthesis. To meet this aim, it is imperative to explore various methodologies and algorithms meant for mapping the EMG signal of different lower limb muscles to different ankle-foot motions. For the development of prosthesis, the following objectives are enumerated:

- Analysis of various muscles movement of lower limb (below-knee)
- Classification of EMG signals from different sites for interpretation of dorsiflexion and plantarflexion ankle movement
- Development of a hybrid classification algorithm
- Development of ankle prosthesis prototype for transtibial amputee and its control algorithm

1.5 Organization of the Thesis

In **chapter 1**, introduction to amputation, lower limb prosthesis, its control, EMG signal generation in humans, and objectives of the present research work have been covered. **Chapter 2** compiles the technical evaluation of ankle-foot prosthesis. It also presents the literature review of the contributions made by the researchers in the field of locomotion identification and human ankle joint angle estimation for prosthesis control. **Chapter 3** provides the details about the methodology opted for the development of a prosthesis prototype. This chapter further presents the experiment design and data acquisition protocols to conduct the study along with the instruments used for acquiring the various signals. **Chapter 4** contains two sections. The first section of this chapter describes the methodology opted for the lower limb muscle selection for non-weight bearing and weight bearing ankle-foot movements. Further, it presents the signal processing applied for muscle selection along with results and discussion. The second section of the chapter presents the methodology used for developing human activity and locomotion prediction module, along with its signal processing, performance measures, and results. **Chapter 5** describes the methodology, signal processing, performance measures, and results of the human ankle joint angle estimation module design. This chapter also presents the development of electrical-actuator based ankle-foot prosthesis prototype development and its control scheme using the estimated ankle joint angle. **Chapter 6** summarizes the conclusions of the presented research work and discusses its potential for future scope.

Chapter 2

Literature Review

This chapter presents an account of the literature covering various aspects of ankle-foot prosthesis development. Section 2.1 presents a brief introduction to the technical evolution of ankle-foot prosthesis. Section 2.2 covers the work done by the researchers in the field of locomotion mode identification of the subject. Further, section 2.3 presents the literature review of lower limb joint angle prediction methods to control the prosthesis.

2.1 Ankle-foot Prosthesis

A prosthesis is considered as an artificial replacement of a missing or malfunctioning body part. The objective of the ankle-foot prosthesis is to provide ankle-foot functionality for a transtibial amputee. The word transtibial amputee refers to a person who got lower leg amputation between the knee and ankle or on the tibia bone, which is the longest lower leg bone connecting knee joint to the ankle joint. The history of leg amputation and lower leg prosthesis is very ancient. The first text of lower limb prosthesis had been found in Rig Veda, an Indian sacred book, written around 3100 B.C. There it is mentioned that an iron leg was fitted to Queen Vishpla after being amputated in a battle [8]. The subsequent section compiles the technological advancements in ankle-foot prosthesis developments. The lower limb prosthesis can be divided into three subgroups: Passive, semi-active, and active prosthesis. Passive prosthesis utilizes gear, clutch, springs, or dampers to achieve human-like gait pattern, whereas the semi-active prosthesis incorporates electronics to controls the mechanical components as per the need of the gait phase. In active prosthesis, the main actuation mechanism of the joint is externally powered (electric, hydraulic or pneumatic) and controlled by the amputee using sensory information.

2.1.1 Passive Prosthesis

In the early era of civilization, the prime focus of the ankle-foot prosthesis was on just restoring the walking ability of the amputee. Such types of prostheses were made up of materials like iron, woods, or bronze. Since then, the materials used to make prosthesis keep evolving slowly. Federal Government's Artificial Limb Program was run between 1954 to 1957 for the research and development of artificial limbs. A revolutionary outcome of the particular program was a Solid-

Ankle Cushion-Heel (SACH) foot. J. Foort and C. W. Radcliffe from the University of California, Berkeley, developed the prototype of the SACH foot. It was made up of wedged heel of cushioning material and an internal keel to assist smooth rolling action. The cushioning material was intended to absorb the impact during the heel-strike. The performance SACH foot was found far better as compared to the uniaxial foot developed by J. E. Hanger in 1861. The uniaxial foot had articulated ankle joint, which makes it more prone to wear and tear. The SACH foot required low maintenance and offered long durability as it had no articulated ankle joints or moving mechanical parts[22,23].

Jaipur foot, developed by Mr. Ram Chander Sharma in 1968, was an improved version of the initial SACH foot. It utilized vulcanized rubber material to provide a slight inversion/eversion movement, which improves its efficiency. It was mainly designed for Indian rural amputees so that the amputee can sit in a squat position, in a cross-legged position, and walk barefoot [24]. The major drawback of Jaipur foot was its heavyweight, which hinders its usability among the amputee population. Indian Space Research Organization (ISRO) at its Vikram Sarabhai Space Centre developed a lightweight composite material, polyurethane (PU), to reduce the weight of Jaipur foot. These PU Foam Jaipur foot were light in weight and could be mass-produced in large numbers in minimum time with improved quality, provide additional comfort, stability, and durability to the amputees [25].

Lee *et al.* proposed a prototype of the elliptical-shank ankle-foot prosthesis. It was made up of single piece thermoplastic material. It utilized Dynamic Elastic Response (DER) of thermoplastic material and provided flexibility at the shank by modulating the cross-sectional area of the shank. Its lightweight and flexible elliptical shank improve gait and provide more comfort to the amputee as compared to SACH foot [26].

Energy Storing and Returning (ESR) feet are also a type of passive prosthesis. It uses a mechanical element (*i.e.*, spring) to stores and releases the energy in different phases of the gait cycle. It provides improved push off so that moving forward becomes easier for the amputee. It was originally designed for the amputees engaged in sports activities like running and jumping. Seattle foot was one of the earliest ESR foot developed by Model and Instrument Works, Seattle, Washington. The basic working principle of Seattle foot was that it worked as a spring that stores the energy by compressing itself during the stance phase (weight-bearing phase of the gait cycle) and releases the stored energy at the TO event to provide recoil and push the body forward [27].

The efficiency of ESR feet improved exponentially with the evolution of composite materials, Computer-Aided Design (CAD) and Computer-Aided Manufacturing (CAM). Flex foot was considered as the first modern ESR foot, made up of flexible carbon fiber. The flexible carbon material facilitates it to store the energy in the whole prosthesis rather than using a single energy storing element. The material also reduces the energy losses and weight of the prosthesis. Some of the commercially available ESR feet are Ossür Flex-foot Modular III, Ossür Flex-foot Variflex, Otto Bock Springlite Foot, and Ossür Flex-foot Talux, *etc.* [28]. Pitkin had developed a Rolling-Joint Prosthetic (RJP) Foot 1995. It provides articulation in the ankle joint at the beginning of DF and nonlinearly increased resistive counterforces at the end of the DF phase. The dynamic performance of RJP foot was found better than SACH and flex foot [29].

2.1.2 Semi-Active Prosthesis

The performance of semi-active prostheses had been improved by modifying its mechanical structure and including active components. A Controlled Energy Storing and Returning (CESR) foot had been developed by the University of Delft and the University of Michigan in collaborative work. It was an energy-recycling foot which captures collision energy during HS and returns it for push-off. It had a separate rear and forefoot components. The rear foot component starts rotating and compressing a coil spring as the heel strike on the ground. When maximum compression had achieved, the rear foot got latched by a continuous one-way clutch. The stored energy was kept trapped and released only if sufficient load is detected on the fore-foot to provide the push-off. The active components used in this prosthesis were one microcontroller and two small motors. These were used to release the energy-storing spring and reset the entire mechanism [30].

A research group from Vrije Universiteit, Brussel, had developed an ankle-foot prosthesis prototype, popularly known as Ankle Mimicking Prosthetic (AMP) foot-1, which provides an extended push-off. It comprised of a planetary gearbox, a spring, two servo pawl, two switches, and a microcontroller. The planetary gearbox and locking mechanism facilitate it to work on different transmission ration between the rotating leg and lever arm which extend and compress the spring during loading and unloading. The microcontroller provides the control over locking and unlocking of the pawls as per the gait phase detected by the two switches [31]. Shepherd *et al.* at Northwestern University, Evanston, had developed a Variable-Stiffness Prosthetic Ankle-Foot (VSPA Foot). It could modulate the ankle stiffness as per the task. The ankle stiffness was varied

by modulating the support position of fiberglass leaf spring using a small motor. The developed prototype was tested for different walking terrains like level, stair, and ramp [32].

Raize ankle-foot and elan foot are the commercially available semi-active ankle-foot prostheses. Both the prostheses have utilized microprocessor-based hydraulic concept. Raize ankle-foot provides user-friendly, adjustable RoM of PF/DF to reduce the force between residual limb and prosthesis, which provides better stability on slippery surfaces, ramp, and uneven terrain [33]. Elan foot used a sensor feedback system, which makes it adaptable for different walking speed and terrains. The resistance of foot varies as per the requirement of activity. It also modulates the DF angle during the swing phase to avoid the possibility of toppling [34].

2.1.3 Active Prosthesis

The active prostheses have electric/hydraulic/pneumatic actuators to provide extra propulsion for the forward moment. Since 2005, MIT Media Lab, Massachusetts Institute of Technology, Cambridge, USA, is continuously working on the advancement of the lower limb prostheses. Au *et al.*, in 2005, presented an experimental study on EMG position-controlled active ankle prosthesis [35]. In 2008, the advanced version of the previously developed prosthesis (MIT powered ankle-foot prosthesis) was tested over the amputee population for level and stair walk. It had an electrical actuator with two springs, one in series of the actuator and one in parallel of it, and had an impedance, force, and position controller. The finite state control method was used to select the controller as per the locomotion and gait phase [36–38].

The U.S. Army Medical Research & Materiel Command funded spring ankle with regenerative kinetics (SPARKy) project of the Arizona State University, Tempe, Arizona, to develop active ankle-foot prostheses for soldier amputee. It developed three versions of prostheses, SPARKy1, SPARKy2, and SPARKy3. SPARKy1 and SPARKy2 had single actuated DoF, whereas SPARKy3 had two actuated DoF. SPARKy1 was purely passive, having no actuator, microprocessor, and power supply. It stored the energy during the stance phase and unclutched the spring during the swing phase to release the energy. In the initial phase, it was tuned only for standing and normal walking. SPARKy2 was more efficient. It was an active prosthesis with brushless motor and linear transmission facilities. It had no gearbox, which significantly reduced its size and weight. Further, to improve the functionality, and one actuated DoF had been added to

the prosthesis without altering its size and weight and named it as SPARKy3. Though, the additional actuator joint of SPARKy3 makes its control system more complex [39,40].

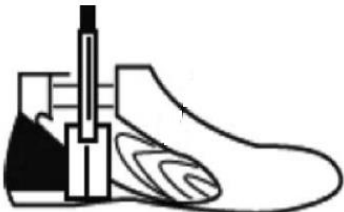
Mechanical Engineering department of Vrije Universiteit Brussel developed a semi-active ankle-foot prosthesis known as AMP Foot 1.0. The design of AMP Foot 1.0 was improved to an active prosthesis known as AMP foot 2.0. It utilized two springs and an electric actuator to achieve storing and controlled release of energy for push-off. Further, the design, actuator, and control strategy of AMP foot-2.0 was improved, and its updated version named AMP foot-2.1. It also provides speed adaptation capability to the subject. The test result of AMP foot-2.1 had shown significant improvement in prosthesis performance during variable speed level walking, but there was still a scope of improvement for walking up and downhill and stair ascent and descent. The latest and updated design of AMP foot is AMP-Foot-3. It uses two locking mechanisms and a compliant crank-slider mechanism to transmit the torque and propulsive force, which improve the functionality and reliability of the prosthesis [41–43]. Vrije University Brussel had also developed an ankle-foot prosthesis prototype using Pleated Pneumatic Artificial Muscles (PPAMs). It provides an active push-off to the amputee during TO and modulates its stiffness with the walking speed. The required stiffness was estimated using the torque-angle characteristic and linear regression model. The PPAM actuators were very lightweight and capable of providing high torque. But, one PPAM can translate only pulling force; hence for one bidirectional joint movement, at least two PPAMs were required in antagonist mode. Moreover, to operate the PPAM pneumatic pressure source was needed, which make the prosthesis bulky and restricted its applicability for real-time use [44].

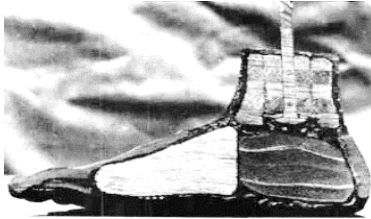
The research group of Peking University had developed a powered segmented ankle-foot prosthesis. It was very close to the structure of the human foot with adaptable stiffness joints, including toe. It was named as Powered transtibial prosthesis with ANkle and TOE joints (PANTOE). All the joints of prosthesis had Series-Elastic Actuator (SEA) made up of DC motor with series spring and a screw transmission mechanism. The optimal stiffness of each spring was selected using mechanical modeling of the structure. Moreover, the toe joint provides additional stability to the amputee. Initially, the prosthesis was controlled using a linearized trajectory control method, and later it was also tested for volitional EMG control [45–48].

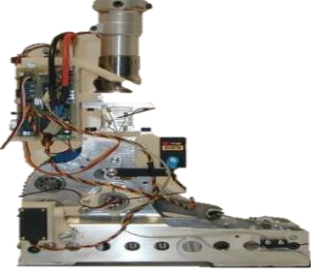
Suzuki *et al.* had proposed a prototype of a power ankle-foot prosthesis. It had a DC motor to provide actuation, motor driver to maintain torque, rotary encoder for angular position measurement, and a microcontroller to implement the control algorithm. A tendon-drive mechanism with the internal model controller was implemented to control the prosthesis. The experimental results had shown a significant improvement in performance over conventional prostheses. However, it was only the preliminary study for experimental purposes, and real-time implementation is still awaited [49].

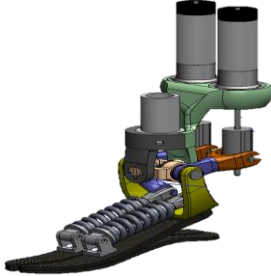
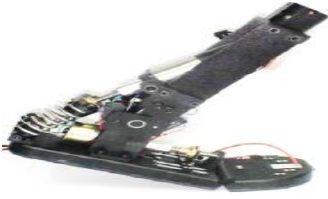
Department of Mechanical Engineering, Marquette University, presented the prototype of a four-bar mechanism-based active ankle-foot prosthesis. The four-bar mechanism linkage design, along with spring and motor, was optimized to provide the strength and required moment during the gait cycle without increasing its size and weight. The prototype had shown satisfactory mechanical strength and improved gait patterns during bench testing. Further, a high-level finite-state controller and low-level Proportional-Integral-Derivative (PID) had been designed to control the prosthesis. The controller served two purposes during the gait cycle; during the stance phase, it controls the motor to provide additional energy for push-off, and during the swing phase, it controls the angular position of the prosthesis to get ready for next gait cycle. A dynamic simulation technique was used to tune the PID controller. The moment generation ability of prosthesis along with its controller had been tested over the Instron testing machine. The results showed that the prosthesis was able to achieve 80% of the desired moment during the gait cycle. However, it can be improved by replacing the active components with higher rating components [50,51].

Table 2.1 Various ankle-foot prostheses and its features

S.No	Ref/Type	Prototype	Features
1	Passive [22]		➤ Non-articulated ankle joint ➤ Internal keel to assist smooth rolling action ➤ Cushioning material absorbed the impact during HS ➤ Heel wedge provides pseudo-PF ➤ The rigid wooden keel provides midstance stability

2	Passive [23]		➤ Articulated ankle joint ➤ Two adjustable bumpers limit and control ankle DF and PF movement ➤ PF bumper permits the foot to contact the floor more rapidly during loading response ➤ Heavyweight ➤ Does not offer more lateral movement ➤ Requires more frequent maintenance
3	Passive [24]		➤ Jaipur foot ➤ Vulcanized rubber material provides slight inversion/eversion movement ➤ Improved performance as compare to SACH foot ➤ An amputee can sit in a squat position, in a cross-legged position and walk barefoot ➤ Heavyweight
4	Passive [26]		➤ Has a flexible elliptical-shank monolimb ➤ Made up of one piece of thermoplastic material ➤ Much lighter in weight as compared to the conventional prosthesis ➤ Provide more comfort to amputee and also the gait is improved ➤ Long term effect of shank flexibility is not there
5	Passive [27]		➤ ESR foot ➤ Spring-like structure to stores and release the energy in different phases of the gait cycle ➤ improved push-off
6	Passive [29]		➤ Articulated ankle joint ➤ The dynamic performance was found better than SACH and flex-foot
7	Semi-active [30]		➤ Controlled Energy Storing and Returning (CESR) foot ➤ captures collision energy during HS and returns it for push-off ➤ The complete foot has two components rear and forefoot components ➤ One microcontroller and two small motors were used to release the stored energy in spring

8	Semi-active [31]		➤ Ankle Mimicking Prosthetic (AMP) foot ➤ The mechanical structure had a planetary gearbox, a spring, and two servo pawls ➤ A microcontroller was used to control over locking and unlocking of the pawls ➤ It regenerates energy during the dorsiflexion phase and releases it over the entire push-off phase
9	Semi-active [32,52]		➤ Variable-Stiffness Prosthetic Ankle-Foot (VSPA Foot) ➤ A cam-based transmission and a fiberglass leaf spring had been used as in mechanical structure ➤ A small motor was used to modulate the support condition of leaf spring and its stiffness ➤ Controlled by tracing the torque-angle curve of ankle-foot
10	Semi-active [33]		➤ Microprocessor controlled (MPC) hydraulic ankle-foot ➤ Adjustable heel height ➤ Adjustable plantar flexion and dorsiflexion range and stiffness ➤ Adapt to uneven terrain ➤ Simulates natural ankle movement and reduces vertical shock ➤ Automatically adjusts to allow maximum dorsiflexion when walking on an incline ➤ RoM for the ankle is 10° dorsal flexion and 18° plantar flexion
11	Semi-active [34]		➤ Microprocessor controlled self-aligning plantar flexion and dorsiflexion ➤ Standing support mode increases resistance when stationary to help improve balance and stability ➤ Adaptable to different walking speed and terrains ➤ Provides extended dorsiflexion during swing phase to increase toe clearance and reduce risk of trips and falls ➤ Provides higher resistance during slop walking for better stability and safety

12	Active [36,38]		➤ Utilized Series Elastic Actuator (SEA) using physical spring in series with drive ➤ Manual EMG triggering based transition control ➤ Two-level finite state machine controller ➤ Only level-ground and stair-descent locomotion are considered. ➤ One Degree of Freedom
13	Active [39,40]		➤ SPARKy (Spring Ankle with Regenerative Kinetics) ➤ brushless motor and linear transmission ➤ Smaller and more powerful brushless motor without the need for a gearbox ➤ Walking speeds over 4 miles per hour ➤ Toe design is considered ➤ Two Degree of Freedom
14	Active [41–43]		➤ Ankle Mimicking Prosthetic (AMP) Foot-3.0 ➤ Adaptive speed using variable stiffness components ➤ A hybrid controller is used ➤ Lightweight actuators are used ➤ Two locking mechanisms and a compliant crank-slider mechanism ➤ One degree of freedom
15	Active [44]		➤ Pneumatic actuators are used ➤ Finite-state controller ➤ EMG based control ➤ Only for level walking with speed adaptation ➤ One degree of freedom
16	Active [47]		➤ Powered below-knee prosthesis with ankle and toe (PANTOE) ➤ Finite-state control strategy ➤ Electric actuator with spring ➤ EMG signal-based control ➤ A linearized trajectory control method ➤ One Degree of Freedom
17	Active [51]		➤ Four-bar mechanism linkage design ➤ Electric actuator with spring ➤ High-level finite-state controller and low-level proportional-integral-derivative (PID) controller ➤ One degree of freedom

2.2 Locomotion Identification

Locomotion identification is one of the integral steps of an active ankle-foot prosthesis control system. This module predicts the locomotion mode of the subject so that the control system modulates the prosthesis parameters in anticipation and provides seamless operation of prosthesis. Locomotion mode methods can be divided into three categories; Kinetic/Kinematic sensor-based, biopotential based and hybrid (mechanical sensors and biopotential).

2.2.1 Kinetic/Kinematic Sensor Based

Kinetic/Kinematic information of the lower limb is captured by using accelerometers, Inertial Measurement Unit (IMU), load cells, and Force Sensitive Resistance (FSR), *etc.* These sensors are portable can be worn comfortably by the user or can be incorporated within the prosthesis. Lei *et al.* presented a preliminary assessment of a neural-network based locomotion identification model. The hip angular velocity and angular acceleration were captured using a gyroscope and accelerometer. To filter the noise, a wavelet filtering technique had been applied to both the sensors and Principle Component Analysis (PCA) for feature extraction. The top nine primary components of both the sensors were used as the feature vector to train a Backpropagation Neural Network (BPNN). The trained network showed average classification accuracy >90% for five locomotion modes. Its performance can be improved by incorporating a fuzzy theory with it [53].

Zhang *et al.* proposed the design of a locomotion identification model using IMU sensors and laser distance sensors. The IMU sensors were used to capture the laser light source location on the human body and the orientation of the foot. The geometry of terrain was reconstructed using these signals, which include terrain height and its distance from the human body. A Decision Tree (DT) classification approach was utilized to classify six locomotion. The proposed system was able to recognize 157 out of 160 tested terrain transitions in the laboratory environment. This particular method further opted as an automatic training tool to control the lower limb prosthesis to enhance the performance of the existing locomotion identification algorithm [54–56].

Young *et al.* presented a locomotion identification method using 13 mechanical sensors, which captured vertical force, KA, ankle joint angle, knee velocity, and ankle velocity. Two Linear Discriminant Analysis (LDA) classifiers were trained for identifying five locomotion modes at HS and TO events, respectively. The classifier was trained using a feature vector having four time-domain features of each mechanical sensor. The results showed a classification accuracy of 84.5%

when only steady-state training data were used, whereas it increased to 93.9% when training data of locomotion transition was included. It was also found that training data of a single analysis window at HS and TO events resulted in better classification accuracy as compared to multiple analysis windows [57]. The particular method of locomotion identification was further implemented using a dynamic Bayesian network classifier by incorporating sensors' prior information besides sensors' current information. This time history information of sensors reduced the classification error rate by 50% [58]. However, these approaches required higher training data to achieve satisfactory performance. To tackle this problem, a user-independent locomotion identification approach had been developed. It utilized a locomotion mode dependent classifier besides the LDA and time history Dynamic Bayesian Neural Network (DBNN) classifier. The mode dependent classifier improved its performance by 60% even for novel user [59].

The research group of Peking University, Beijing, had proposed various approaches for locomotion identification. Chen *et al.* proposed a multi-sensor fusion based two-level locomotion recognition strategy. It utilized two insole foot pressure sensors, three IMU, and four gait phase-dependent LDA classifiers to classify six locomotion modes. The feature vector was constructed by using six time-domain features of each sensor. The average classification accuracy for steady locomotion was found as $99.71 \pm 0.05\%$. Further, the features in the feature vector were also optimized to improve the computational performance of the model [60,61]. In another approach, the temporal foot pressure pattern had been investigated for locomotion identification. A pair of foot insole was designed to measure discrete contact force with four pressure sensors at the selected location on each insole. A sequential locomotion identification strategy with DT and LDA classifier had been designed. The proposed method depicted average classification accuracy as 98.8% and 98.4% for abled and amputee subjects, respectively [62].

Yuan *et al.* proposed a fuzzy logic locomotion identification methodology using the inclination angle of foot and shank in various phases of the gait cycle and foot strike sequence. The parameters mentioned above were measured with the help of two gyroscopes, accelerometers, FSR, and timer. The result showed the average classification accuracy of $98.74 \pm 0.32\%$ for five locomotion modes [63]. A similar fuzzy logic classifier along with hip joint angle and foot center of pressure had been utilized by Parri *et al.* to classify seven locomotion modes. It was a two-level classification approach that showed an average classification accuracy of 99.4% for abled body subjects [64].

Further, the study was extended to the three-level classification approach using a Quadratic Discriminant Analysis (QDA) classifier. In this approach, the first classifier was trained to classify between standing and ambulation mode. The second level of classification was done to identify the gait cycle phase. At last, in the third level of classification, two classifiers were trained to classify locomotion modes for the stance and swing phase of the gait cycle, respectively. The average classification accuracy showed by the QDA classifier was 96.40% and 91.21% for the swing and stance phase of the gait cycle [65].

Shahmoradi *et al.* explored a preliminary design of a fuzzy sequential locomotion identification model using three IMUs and two FSR. FSRs were deployed to detect the stance and swing phase of the gait cycle, whereas the IMU signal was applied to train the classifier. The IMU had 6-DoF. For each DoF, four time-domain features were extracted. Hence, each feature vector contained 72 features. The average classification accuracy achieved over five locomotion modes was 95.8% and 86.5% for user-specific and user-independent classification, respectively [66].

Chinimilli *et al.* proposed a single mechanical sensor based two-dimensional feature space approach of locomotion identification. One 9-DoF IMU sensor module had been deployed to capture thigh angular position and frequency. Angular position and frequency information were utilized as two-dimensional feature subspace. The performance of Support Vector Machine (SVM) and k-Nearest Neighbor (k-NN) classifiers were compared for six locomotion modes under controlled and uncontrolled environment. Both the classifiers performed equally well for both the environmental conditions with an average classification accuracy of 98.1% and 93.3%, respectively [67]. The same method had been applied using a phase variable classifier. It compared the divergence rate of the instantaneous feature space curve to the local feature space curve of each locomotion. The average classification accuracy of the phase variable classifier had been found as $98.3 \pm 3.0\%$ and $97.7 \pm 3.5\%$ for subject-specific and non-subject specific training dataset, respectively [68].

Godiyal *et al.* proposed a force myograph (FMG) based approach for locomotion identification. In this method, an array of resistive force sensors had been used to capture the modulation in volumetric changes in thigh muscles while performing various locomotion. The proposed method also utilized the LDA classifier as a learning algorithm. The average classification of the proposed method for five locomotion modes was $99.5 \pm 0.5\%$ for the subject-specific classifier [69,70].

Zheng *et al.* proposed a noncontact capacitive sensing (C-sene) system for locomotion identification. It had an array of sensors placed in between prosthesis and residual limb. It modulates the capacitance as the space between the prosthesis and residual limb varies. A variety of phase-dependent classifiers were trained and tested for six different types of locomotion. It utilized 42 features (6 sensors $\times$ 7 features) of the C-sene array signal. The proposed method was capable of making the continuous decision for all types of locomotion with an average classification accuracy of 96.3 % for the swing phase and 94.8 % for the stance phase using the LDA classifier. Further, the developed system was tested and modified for a variety of other lower limb activities and real-time prosthesis control [71–75].

2.2.2 Biopotential Based

Biopotentials are electrical signals generated through physiological processes taking place within the body. These are generated by the electrochemical activity of an excitable cell. The most common biopotential opted for the man-machine interface is EMG. It can be recorded noninvasively from muscles, which eventually reflects the activity of particular muscle during limb movement. There are quite a few studies which rely only on EMG signals for locomotion identification task. Peeraer *et al.* explored the possibility of utilizing the EMG signal of lower limb muscles to identify the locomotion modes. The EMG activity of six lower limb muscles had been recorded for three locomotion modes, which include level walking, ramp ascent, and ramp descent. A gait phase-dependent threshold-based classifier was also proposed, which relies on muscle peak activity. The results showed the very healthy possibility of utilizing EMG signals for locomotion classification, even with only three lower limb muscles [76]. A similar analysis of EMG signals was also presented by Dwen *et al.* for five locomotion modes and variable walking speed. Initially, EMG signals of eight lower limb muscles were analyzed, and the EMG signal of only three muscles was utilized for locomotion identification. A DT based classification algorithm was developed, which utilized five features of each muscle for the classification task. The average classification accuracy achieved was 94.25% and 87.48% for abled subjects and amputee, respectively [77].

Au *et al.* of MIT Media Laboratory had proposed an EMG triggering based locomotion indication strategy to control the lower limb prosthesis. It was a manual technique in which the subject had to flex gastrocnemius muscle during the swing phase of the gait cycle to change the locomotion

mode from level walking to stair descent and tibialis anterior muscle to come back to level walking. It was only designed for only two locomotion modes. Moreover, it was a burdensome technique for the subject and required very much practice [36]. Further, the same research group proposed an EMG and machine learning-based automatic locomotion identification technique. It utilized the gait phase-dependent Naive Bayes (NB) classifier to classify four locomotion modes for transfemoral amputees and two locomotion modes for the transtibial amputee. EMG signal of ten lower limb muscles was recorded, and eight time-domain features for each muscle were extracted. Later a wrapper-based feature selection algorithm was applied to optimize the number of features in the feature vector. The feature selection algorithm reduced the number of features significantly to four features and achieved about 100% classification accuracy [78].

Huang *et al.* presented a pilot study for locomotion identification utilizing the EMG signal of sixteen lower limb muscles. The study included seven locomotion modes and applied four gait phase-dependent classifiers. The performance of LDA and Neural Network (NN) classifiers were compared for eight subjects. Seven features for each EMG channel were extracted for formulating the feature vector to train the classifiers. The LDA and NN classifier showed no statistically significant difference in performance, and their average performance was found as 92.22% [79].

Miller *et al.* proposed a strategy for locomotion identification using the EMG signal of four lower limb muscles. In the proposed strategy, it was assumed that the information of the complete gait cycle could be encapsulated in its three subwindows. Hence, only three subwindows over the complete gait cycle were utilized for training the classifier. Five time-domain features were calculated for each EMG channel, so the feature vector contained a total of 60 features for one complete gait cycle. The performance of LDA and SVM classifiers were compared to classify seven locomotion modes for abled and amputee subjects. The performance of both the classifiers was found comparable without any statistically significant difference. The average classification accuracy achieved was 97.9% and 94.7% for abled and amputee subjects, respectively [80].

Kim *et al.* presented a real-time locomotion identification method employing correlation feature analysis of EMG signals. Four lower limb muscles were opted to acquire the EMG signal for three locomotion modes. Six time-domain features of each EMG signal were calculated, and further, by using these features for every locomotion mode, six weighted sub-correlation filters were designed to classify locomotion modes. The average classification accuracy came out as 85.89%, 96.47%,

and 96.37% for level walking, for stair ascent and stair descent, respectively. However, this sub-correlation method was found to be computationally expensive as compare to conventional LDA and SVM classifiers [81]. Joshi *et al.* proposed an EMG spectrogram approach with a rule-based classifier to classify locomotion modes. EMG signal of seven lower limb muscles had been used to classify three locomotion modes. The proposed model showed an average classification accuracy of 80% for non-amputee subjects. Further, the classification accuracy of the model was improved to 89% by incorporating time history information of locomotion modes. To cut off the computational burden of the system, three muscles depicting the least contribution in classification accuracy had been discarded, and it reduced its computational time by 42.8%. However, the average classification performance was also reduced by 14.4% [82].

Afzal *et al.* had proposed a novel muscle synergy-based approach to identify locomotion modes using lower limb EMG signals. The basic idea of the proposed method was to replicate the biological human central nervous control system of muscles to perform a limb movement. Muscle synergies were considered as a fixed relative activation level of different muscles during various locomotion. The muscle synergies were extracted from the Root Mean Square (RMS) value of nine muscles during two critical events of the gait cycle. The nonnegative matrix factorization technique had been applied to estimate the muscle synergy matrix for each locomotion. The proposed muscle synergy approach showed average performance as 88% classification accuracy for five locomotion modes. However, the results of conventional LDA and SVM classifiers were found comparable to the muscle synergy-based approach [83].

In recent years, electroencephalogram (EEG) had emerged as a sophisticated tool to map cortical activity to various locomotion. A study presented by Brantley *et al.* [84] had shown a very high correlation between lower limb muscle EMG and EEG signals for different locomotion. The study was further extended, using source localization and clustering technique to accurately get the location of cortical activity locations during locomotion. The results revealed the participation of the left and right occipital lobe, posterior parietal cortex, and central sensorimotor cortex. Their spectral power changes with the demand of the motor task. The results were directly applicable for locomotion identification, as EEG can be captured noninvasively. However, this study is in a very early stage, and still evident results are not there [85–87]

2.2.3 Hybrid Information Based

Hybrid information based locomotion identification methodology utilized EMG as well as kinetic/kinematic sensors information for locomotion identification. Hence, it carries advantages of both types of sensors. Huang *et al.* proposed a neuromuscular and mechanical sensor information-based locomotion identification methodology. It utilized EMG signal of nine muscles of gluteal and thigh as neuromuscular information and a 6-DoF load cell as a mechanical sensor to capture foot ground reaction force and moment information. Multiple gait phase-dependent SVM classifiers were used to identify five locomotion modes. The classifiers were trained using a feature vector consisting of four time-domain features of each EMG channel and three features of each DoF of the load cell. The result had shown the best classification accuracy as 99% and 95% for the stance phase and swing phase, respectively [88,89]. The performance of the proposed method was further improved by including previous locomotion probability information with the LDA classifier. Its real-time implementation on Field Programming Gate Array (FPGA) system was also done in a lab environment [90,91]. The computational burden of the model was optimized by selecting the most informative sources. The results suggested that EMG and ground reaction force are more informative as compared to prosthesis kinematic information [92]. Further, the robustness of the particular locomotion identification model was enhanced by incorporating an adaptive classification algorithm. An entropy-based adaptation algorithm was developed and implemented. The results had shown that with the adaptation algorithm, the model performance remained unaltered even with the variation in intersession EMG signal [93].

Afzal *et al.* proposed a lower limb neuromuscular and joint kinematic signals fusion-based locomotion identification method. The neuromuscular information was captured from five lower limb muscles as the EMG signal, and three kinetic sensors were deployed to record acceleration, hip angle, and KA. LDA classifier was trained using a feature vector having six time-domain features of each EMG channel and five time-domain features of each kinetic sensors. The algorithm had shown average classification accuracy as 97% over five locomotion modes. Also, the results revealed the importance of the hip joint angle and KA for locomotion identification [94]. Joshi *et al.* proposed a structure to identify terrain type and its direction during locomotion transition. It utilized EMG signal from seven lower limb muscles and two 3-axis accelerometers to record shank and foot acceleration during the transition. Information from EMG and accelerometer sensors had been extracted using eight features and seven features for each sensor,

respectively. This study revealed that the transitions were better classified as terrain type rather than direction type. Moreover, the EMG and accelerometer signal was found complementary to each other during the transition [95].

Research work presented by Ai *et al.* had utilized the fusion of lower limb EMG and accelerometer signals to predict locomotion modes. A median filtering curve fitting methodology was applied to remove accelerometer noise. Time-domain information and wavelet coefficients of EMG signal were used as features. Whereas, for the acceleration signal, a dynamic time warping distance was used for feature extraction. The study evaluated the performance of LDA and SVM classifiers for five locomotion modes. The results proved the superiority of fusion-based classification with the average classification accuracy of 95% as compared to only EMG or accelerometer signals [96]. A similar method was proposed by Kyeong *et al.* in which the EMG signal of four lower limb muscles of both the legs with three mechanical sensors had been used to classify five locomotion modes. Four features for each joint angle of leg and four features for individual EMG channel had been extracted to train a Bayesian-LDA classifier. The results showed average classification accuracy as 96.8% and 98.6% for one leg and both leg approach [97].

Young *et al.* developed an EMG and mechanical sensor signal-dependent locomotion identification algorithm. It utilized the EMG signal of seven lower limb muscles along with 13 mechanical sensors information of prosthesis. Ten time-domain features for each muscle were calculated, and for mechanical sensors, four features for each sensor. The performance of the proposed algorithm had been evaluated with and DBNN classifiers individually for five locomotion modes. LDA classifier depicted the best classification accuracy as 90%, and for the new subject, it reduced to 65%. Further, to improve the performance of algorithm time history information based DBNN classifier was trained. With the DBNN classifier, the best classification accuracy 99% had been achieved [98–100]. In a subsequent study, the effect of additional mechanical sensors information on the performance of the algorithm had been analyzed. The results indicated that additional sensors improved the performance of the algorithm for the steady-state as well as for transitional locomotion identification. However, due to additional sensors, the computational, as well as the circuitry burden of the system, increased [101]. Further, the offline performance of the algorithm for locomotion specific LDA classifiers had been evaluated by incorporating contralateral leg neuromechanical signals as additional information. The particular strategy is shown best classification accuracy as 97.52% for five locomotion modes [102].

In recent years image-processing based locomotion recognition techniques had been explored by various researchers. Massalin *et al.* proposed a user-independent locomotion identification structure using recursive features of image and SVM classifiers. The results showed the best result as 94.1% classification accuracy for three locomotion modes [103]. A preliminary study conducted by Laschowski *et al.* designed a chest-mounted camera system with a deep learning algorithm to recognize locomotion mode out of level ground and stair walk. The particular study demonstrated the best classification performance as 94.85% classification accuracy [104]. Khadem *et al.* and Zhang *et al.* also proposed a similar technique with an additional IMU sensor. The IMU sensor was used to capture the standstill image and which improves the model performance up to 99% classification accuracy [105–107].

2.3 Lower Limb Joint Angle Prediction

In recent years, the position and orientation control method of the prosthesis has been evolved as an effective and efficient control method. Although, it has been extensively used for upper limb rehabilitative and assistive devices control. The research community is also adapting this control method for lower limb prosthesis control. The source of the signal to estimate the lower limb joint angle is of various types like; mechanical sensors, vision sensors, EMG, EEG, *etc.* The subsequent literature compiles the contribution made by the researcher to predict lower limb angular position estimation. Depending on the source of signal used to estimate the lower limb joint angle, the methods available in the literature are classified in two broad categories; kinetic/kinematic signal based methods and EMG signal based methods.

2.3.1 Kinetic/Kinematic Signal Based Methods

IMU had evolved as a portable and cost-effective wearable sensor to capture kinematic information of human limb joints. This kinematic information can be processed further to estimate kinetic information of human limb joints. Bakhshi *et al.* presented multi IMU signals based KA estimation technique. The results of the proposed method were compared with the infrared motion capture system for four activities; sitting down and standing up, leg swing while seated position, knee flexion while standing, and squatting. The average error, standard deviation, and correlation coefficient were 1.80°, 7.94°, and 0.97, respectively. However, a deterioration in performance was registered with variation in speed and type of activity [108]. Adopting a similar methodology, Watanabe *et al.* developed a portable wireless module to estimate all lower limb joint angles (Hip,

Knee, and ankle). The performance of the developed module was tested against the optical motion measurement system for level walking activity. The average Root Mean Square Error (RMSE) was found below 4° , and the average Correlation Coefficient (CCoef) was above 0.85 [109].

Milica *et al.* proposed a digital filtering method to estimate the knee and ankle joint angle using multiple accelerometers signals. The proposed method was validated using an electronic goniometer signal for walking at different walking speeds on the treadmill. This method had shown the range of RMSE as 3° to 7° for KA and ankle joint angle it was in the range of 2.5° to 5.5° . However, for real-time implementation of a particular method, a delay of one stride had been observed [110]. The performance of the accelerometer-based method was improved by incorporating the gyroscope signal with it. Seel *et al.* proposed a joint angle estimation method using an accelerometer and gyroscope signal. The main advantage of this method is that the sensors can be placed at any location of the limb segment, *i.e.*, the alignment of sensors on different segments was not required. Average RMSE was found at 3.30° and 1.62° for knee and ankle joint angles, respectively [111]. Rouhani *et al.* utilized four IMU sensors to estimate the foot segment angle during walking at a different speed. The proposed method was validated against a stationary optoelectronic motion capture system. A forward and backward strap-down integration technique was used to estimate the foot joint angles. The average RMSE and CC over different running speeds were found as 1° and 0.93, respectively [112].

The incorporation of artificial intelligence with sensors signal improved the performance of the prediction model, many folds. Joshi *et al.* presented a method of estimating KA using KA of the contralateral leg. A 1st order Sugeno type Adaptive Neuro-Fuzzy Inference System (ANFIS) was trained to estimate KA at different walking speeds. This method had a direct application in echo control of the transfemoral prosthesis. The average RMSE over different walking speeds was 3.4° [113]. A synergetic Gaussian process regression model had been developed by Eslamy *et al.* to predict knee ankle joint angle and generated torque. The developed model mapped the shank angular velocity and shank angle to the ankle joint angle. The result showed average RMSE in the range of 1° to 4° and CCoef in the range of 0.82 to 0.90 while estimating KA at different walking speeds [114]. Dey *et al.* had also proposed a similar approach for predicting ankle joint angle and moment using angular position and angular velocity of hip and knee. This method uses a support vector regression method as a learning algorithm. The experimental results had shown promising performance as 1.29° RMSE and 0.99 CCoef for level walking at nominal speed [115].

2.3.2 EMG Signal Based Methods

Human lower limb joint angles during walking are often referred to as gait angles in literature. Lower limb joint angle prediction models using EMG signal in combination with machine learning algorithms had registered satisfactory performance in the literature. Studies presented in [116–120] explored the possibilities of KA prediction using EMG signal by applying Artificial Neural Network (ANN), Dynamic Recurrent Neural Network (DRNN), and General Regression Neural Network (GRNN). The results obtained in these studies proved the efficient applicability of NN based nonlinear models to predict human lower limb joint angles. Zhang *et al.* proposed a 20th order nonlinear model to estimate human lower limb joint angles using the EMG signal from seven lower limb muscles with BPNN [121]. The average RMSE was found $<9^\circ$ and $<6^\circ$ for a treadmill exercise and leg extension exercise, respectively. This study was further extended by using Least Squares-Support Vector Regression (LS-SVR) method [122]. Integral Absolute Value (IAV) of time-delayed EMG signal (of order 15) was used as a feature to train the LS-SVR model, and average RMSE was found $<5^\circ$ for the treadmill as well as leg extension exercise.

The study presented in [123,124] implemented the auto-regressive integrated moving average with exogenous input (ARIMAX) model and nonlinear autoregressive model to estimate the ankle joint angle. The ARIMAX model had shown the best CCoef as 0.86 for static DF and PF movement. Whereas, the nonlinear autoregressive model showed RMSE $<6^\circ$ for walking activity with 100 msec time history information. Feature fusion is an efficient method of extracting information from the EMG signal. The experiment presented by Tang *et al.* utilized a multi-feature fusion approach with BPNN to predict KA [125]. Time-domain features and fuzzy entropy of wavelet of EMG signal were used to extract the information from the EMG signal. The average prediction error achieved was in a range of 3.25 to 11.65% for three different activities, namely, standing up, flexion, and extension. In a similar study presented by Huihui *et al.*, time-domain features were utilized to predict ankle joint angle while random forest (RF) as a learning algorithm [126]. The results of the RF algorithm showed its superiority over the NN algorithm for ankle movements.

Borges *et al.* integrated the gyroscope (velocity) signal of the lower limb with the EMG signal using Kalman filter correction, and NN was used as a learning algorithm to predict KA [127]. The results showed a considerable improvement in performance over the EMG signal-dependent model. However, this approach results in higher convergence time and computational complexity,

which ultimately increase the response time of the model. Recently, Dhindsa *et al.* proposed a quantization-based approach to evaluate KA using the EMG signal. The knee RoM was quantized into five levels/class, and a pattern recognition approach for predicting the level/class was implemented. The results showed the best classification accuracy as $92.2 \pm 2.2\%$ with the SVM classifier [128].

The literature compiled in this chapter concludes that active ankle-foot prostheses are more efficient and effective as compare to passive and semi-active prostheses. Ankle-foot prosthesis with one-DoF actuated joint providing DF/PF movement is sufficient for daily life locomotion. Hybrid (EMG signal in combination with kinetic/kinematic information) signal with machine learning algorithms is an effective way to identify the human activity/locomotion intention. Moreover, time-domain features with phase-dependent classification approach results in better performance. Literature regarding lower limb joint angle estimation suggests of utilizing EMG signal with NN based learning methods.

Chapter 3

Methodology and Data Acquisition Protocols

This chapter describes the methodology opted to develop the prosthesis prototype. It also presents the material & methods utilized and experiment design to conduct the research work. Section 3.1 briefly describes the methodology applied for the prosthesis development. The subsequent sections 3.2 describes the instrumentation and data acquisition protocols to carry out the present research.

3.1 Methodology

The prime objective of the presented work is to develop a prototype of a hybrid ankle-foot prosthesis. Figure 3.1 shows the block diagram representation of the methodology adopted to achieve objectives stated in section 1.4.

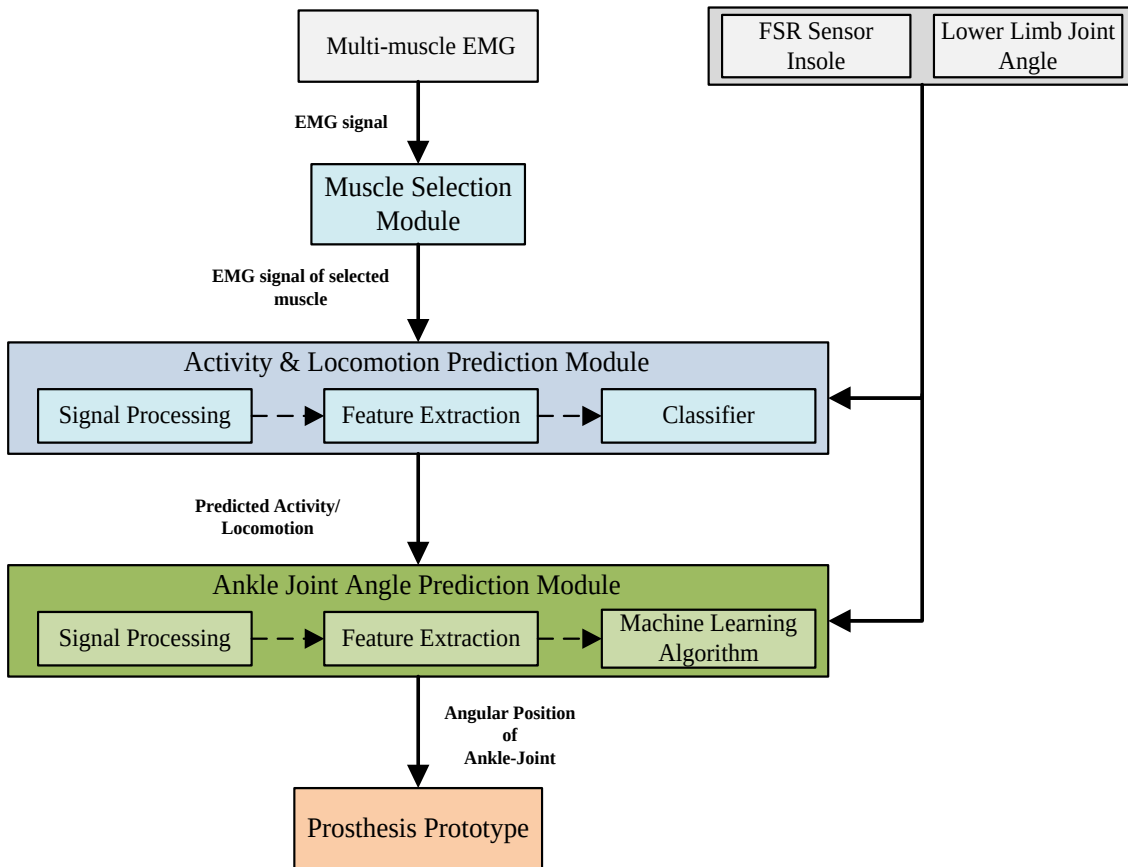


Figure 3.1 Methodology adopted for the development of ankle-foot prosthesis

EMG, lower limb joint angle, and gait phase information of the subject has been used to operate the prosthesis. A multi-channel EMG signal acquisition module has been used to acquire EMG signals from various lower limb muscles (below-knee and above-knee). The lower limb joint angle information has been recorded using IMU units, and the gait events (HS and TO) have been detected with FSR sensors. All the aforementioned signals have been recorded for various lower limb activities and locomotion to design, train, and test the prosthesis.

The human musculoskeletal structure is highly redundant. Therefore, the recorded EMG signal of various lower limb muscles has been analyzed to select the appropriate set of muscles for ankle joint movements. The muscles have been selected based on their reliability and consistency of EMG signal for repetitive DF and PF ankle movements. Here, a hierarchical control structure/sequence is implemented. This control structure consists of two control modules, namely, high-level and low-level control modules. The high-level control module is at the top of the hierarchy and sometimes also termed as a high-level controller. It perceives the user's activity and locomotion intention like standing, level walking, stair ascent/descent, or ramp ascent/descent. The output of the high-level control module is further transmitted to the low-level control module. The low-level control module is also referred to as a low-level controller. The output of the low-level control module depends on the input of the high-level control module. This control module estimates the desired position/torque/velocity of the prosthesis for a given set of inputs. An activity and locomotion identification module has been designed to predict the activity and locomotion intention of the subject. This module serves as the high-level controller of the prosthesis and provides movement anticipation ability to the prosthesis. It utilizes the EMG signal as a source of neural information and KA signal to predict activity and locomotion intention of the subject. As shown in Figure 3.1, it has three subsystems, namely; signal processing, feature extraction, and classifier. In the signal processing subsystem, the filtering of input signals has been done to remove the noise. After that, the filtered signal passed through the feature extraction subsystem. In this subsystem, the appropriate information/feature from filtered signal has been extracted to construct the feature vector. The feature vector has been used as the input to train and test the classifier.

Further, an ankle joint angle estimation module has been designed to estimate the angular position of the ankle joint. It has three subunits, namely; signal processing, feature extraction, and machine learning algorithm. An individual angle estimation module has been trained and tested for each locomotion mode. It requires EMG signal, KA, and locomotion information as an input to estimate

the ankle joint angle. This module is considered as a low-level controller of the prosthesis, which provides the desired angular position of the prosthesis. Finally, an electrical actuator operated prosthesis prototype has been realized and controlled using the predicted angular position information in the laboratory environment.

3.2 Data Acquisition Protocol

The literature strongly emphasized using bio-potential signals along with the mechanical sensors signals to achieve efficient control over prosthetic devices. Hence, for current research work EMG, lower limb kinematics, and gait events have been acquired. Lower limb joint angles (knee and ankle) have been calculated using three, 6-DoF, IMU sensor (MPU-6050) signals attached to the mid-position of the thigh (IMU1), shank (IMU2), and foot (IMU3) respectively of the subject. Each IMU sensor provides accelerometer and gyroscope signal in x, y, and z-axis. The gyroscope provides the angular velocity as an output, so the joint angle was calculated as integral of the difference between two IMU outputs, in which the sensors were attached to the adjacent segments, given by Eq. (3.1).

$$\theta = \int (\omega_1 - \omega_2) dt + \theta_a \quad (3.1)$$

where, ω_1 and ω_2 are the angular velocities measured with the gyroscopes of IMU1 and IMU2 respectively. θ_a is the initial angle calculated from acceleration data in sagittal plane, given by Eq. (3.2).

$$\theta_a = \tan^{-1} \left(\frac{g_{z1}}{g_{x1}} \right) - \tan^{-1} \left(\frac{g_{z2}}{g_{x2}} \right) \quad (3.2)$$

where, g_x and g_z are acceleration data of IMU1 and IMU2 in the sagittal plane. The knee angle has been estimated using the signal of IMU1 and IMU2, whereas the ankle joint angle has been estimated using IMU2 and IMU3. All the aforementioned steps were implemented in MATLAB for knee and ankle joint angle estimation individually [129,130]. These joint angles have been utilized for further analysis in this research work. FSR sensor foot insole has been used to capture HS and TO events of the gait cycle. EMG signal has been recorded using a multichannel EMG acquisition system developed around ADS 1298 [131]. Ag-AgCl disposable electrodes have been used in a differential configuration, keeping the reference electrode on the patella. The sampling frequency for EMG, IMU, and FSR sensors has been kept at 1000 Hz [88,89]. SENIAM

recommendations have been followed for skin preparation, muscle identification, and electrode placement [132]. Figure 3.2 shows the picture of the fully instrumented subject.



Figure 3.2 Picture of the fully instrumented subject

The data acquisition has been conducted during the two experiments, and for each experiment, ten subjects have been recruited. All the subjects who participated in the research work were volunteers and had no history of neural disorders. The signal recording protocol was explained to all the subjects individually. Further, written consent was signed by each subject before the experiment. They were permitted to withdraw at any time during the data collection. The method adopted for signal acquisition in the present research work was purely non-invasive. The experiment procedure adopted was in accordance with the Helsinki declaration, 2013, and duly approved by the institutional research board.

The signal recording protocol has been designed to explore the lower limb muscle activation pattern during various activities. Two experiments have been designed for current research work, namely; experiment-1 and experiment-2. Experiment-1 has been focused on isolated ankle joints motions during static conditions. Whereas, in experiment-2, the dynamic activities (locomotion) having compound lower limb motions have been covered.

3.2.1 Experiment-1

The prime objective of experiment-1 is to correlate isolated ankle joint movements with EMG signals of below-knee muscles. The outcome of a particular experiment provides a set of muscles having a sustainable EMG signal for non-weight bearing as well as for weight bearing ankle joint movements. The two primary ankle movements, DF, and PF were considered for this experiment. Ten subjects were recruited to record EMG signals from their six-lower limb below-knee muscles (TiAn, Gast, Sole, TiPo, PeBr, and PeLo). Table 3.1 shows the anthropometric information of subjects recruited for experiment-1.

Table 3.1 Anthropometric information of subjects for experiment-1

S. No.	Sub. ID	Age (Yrs.)	Weight (kg.)	Height (cm)
1	S1E1	28	60	168
2	S2E1	35	61	167
3	S3E1	27	56	169
4	S4E1	25	77	165
5	S5E1	37	67	167
6	S6E1	40	75	171
7	S7E1	22	77	173
8	S8E1	25	52	170
9	S9E1	34	71	173
10	S10E1	31	59	168

The signal acquisition protocol had two phases; in the first phase, the EMG signal was recorded for non-weight bearing ankle movements (DF/PF), whereas in the second phase, the signal was

recorded for weight bearing ankle movements (DFW/PFW). Figure 3.3 shows the ankle movements during the signal recording of experiment-1. The protocol followed for data recording was as follows:

Phase 1

- Subjects were instructed to sit straight on the table with hanging legs in a comfortable position. The subjects were free to take support from the back of his/her palm to keep himself/herself in a comfortable position
- The subject was trained for each ankle movement after explaining him all the ankle movements (DF/PF)
- After training appropriate resting time was provided
- The sample recording for each movement was started when the ankle was in a neutral position and stopped after achieving the neutral position again while completing the complete RoM of a particular movement and holding the peak position for 3 seconds
- Twenty samples of each ankle movements were recorded one by one
- If the subject demanded, appropriate resting time was provided in between sample recording

Phase 2

- Subjects were asked to stand up straight on both legs comfortably
- Subjects were trained for each ankle movement after explaining him/her the ankle movements, i.e., DF and PF, with bodyweight (DFW and PFW). DFW is standing on the heel while keeping the toes towards the tibia. PFW is standing on the toes while keeping the whole body straight
- After training appropriate resting time was provided
- The sample recording for each movement was started at a standing (neutral) position when heel and toe both were touching the ground
- The subjects were asked to completing the ankle joint movement while holding the peak position for 3 second
- The sample recording was stopped when the subject ankle movement regain the neutral position
- Twenty samples of each movement were recorded one after another
- No resting time between the sample recordings was provided so that the acquired signal can be used for the muscle fatigue assessment

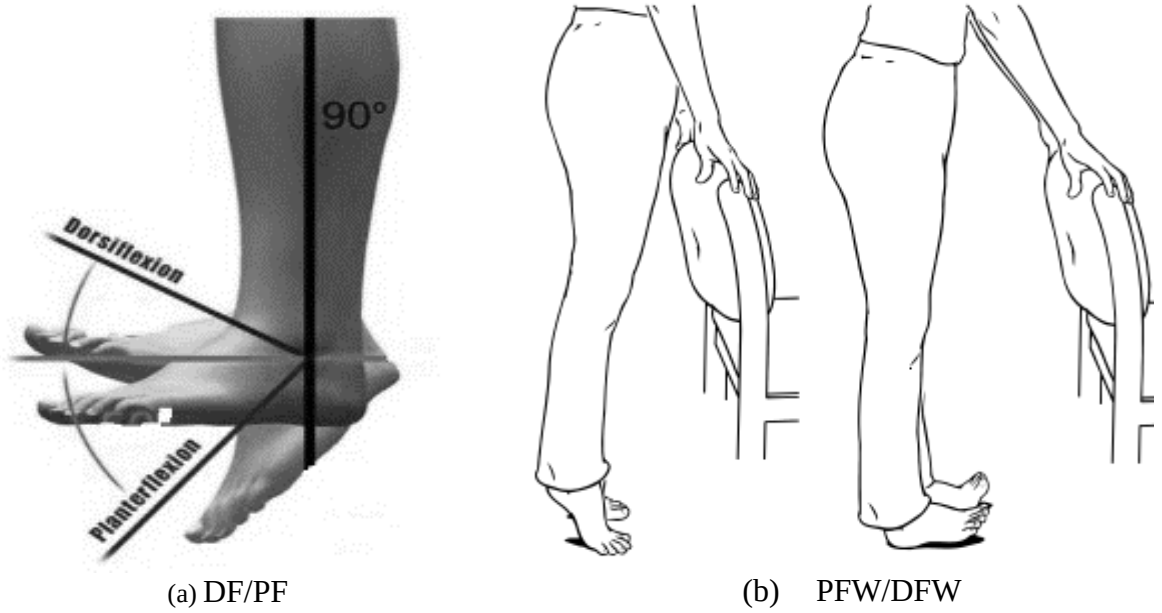


Figure 3.3 Illustration of ankle movements used in experiment-1

3.2.2 Experiment-2

Experiment-2 was designed to acquire the signals for different dynamic lower limb activities. Figure 3.4 illustrates the daily life activity % of a healthy subject over a period of 12 hours after waking up [133]. It has been observed that a major part of daily life is occupied by Sitting (SIT), Standing (STD), and Walking (WLK) activities. The walking activity includes different locomotion like Level Walking (LW), Stair Ascent (SA), Stair Descent (SD), Ramp Ascent (RA), Ramp Descent (RD), *etc.* During sitting and standing activities, there is merely any participation of ankle movement. However, for walking activity, the subject has to pass through the standing position/activity. Hence, for the present experiment, STD and WLK activities have been considered. WLK activity included five locomotion LW, SA, SD, RA, and RD. Figure 3.5 depicts the steady-state locomotion and locomotion transitions considered in this research. Table 3.2 summarizes the anthropometric information of all the ten subjects who participated in experiment-2. For each subject, EMG signal from six lower limb muscles (TiAn, Gast, VaLa, ReFe, Semd, and BiFe), knee and ankle joint angle along with FSR foot insole signal were recorded. Dataset of this particular experiment has been utilized for locomotion identification module design and ankle joint angle estimation.

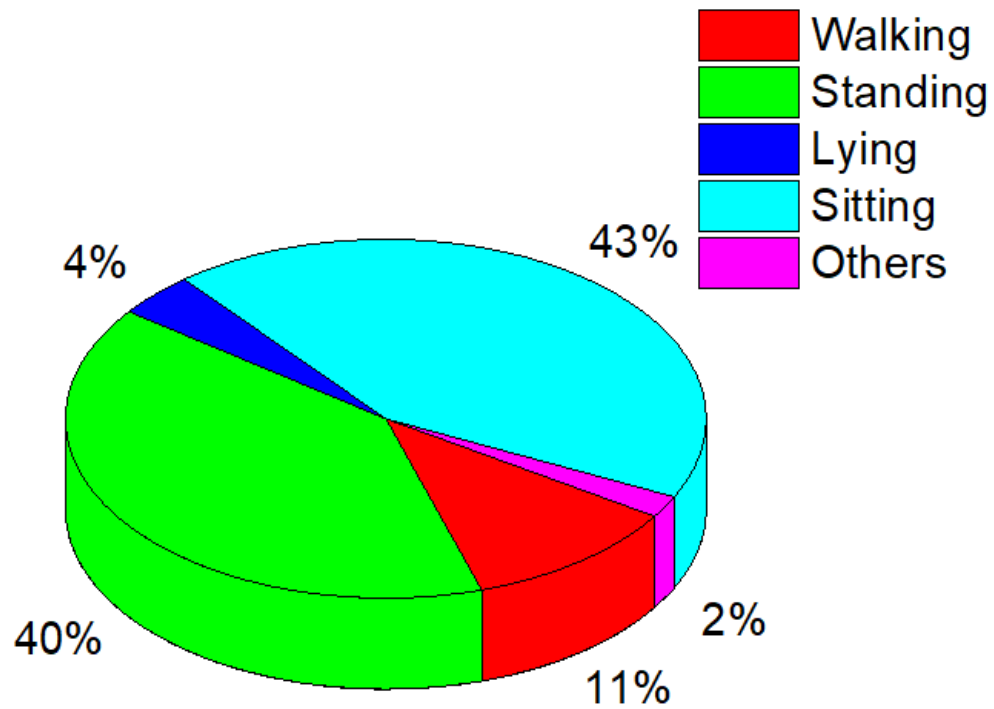


Figure 3.4 Activity % of the healthy subject during 12 hours after waking up

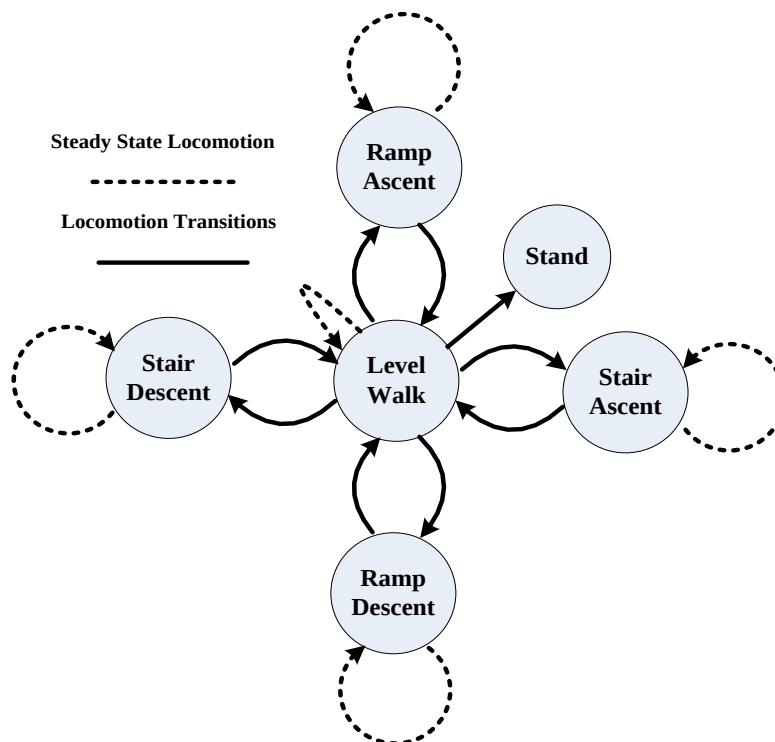


Figure 3.5 Locomotion modes considered for presented research work

Table 3.2 Anthropometric information of subjects for experiment-2

S. No.	Sub. ID	Age (Yrs.)	Weight (kg.)	Height (cm)
1	S1E2	32	74	172
2	S2E2	26	65	173
3	S3E2	28	66	168
4	S4E2	34	69	170
5	S5E2	38	78	178
6	S6E2	27	60	173
7	S7E2	24	64	165
8	S8E2	23	54	170
9	S9E2	25	78	173
10	S10E2	35	59	168

The experiment had two activities STD and WLK. Further, WLK activity had five different locomotion modes (LW, SA, SD, RA, and RD) in a sequence, as shown in Figure 3.6. The protocol followed for data recording was as follows:

- All subjects were asked to walk on the terrain circuit as his/her preferred walking speed until he/she got familiar with the terrain circuit
- Before beginning the signal recording appropriate resting time was provided to each subject
- As the signal recording started, the subject was instructed to stand in relax condition (without any limb movement) for 60 secs, and then a sound trigger was provided to start walking on terrain circuit
- After completing the entire terrain circuit, the subject was asked to stop and keep on standing for 60 sec. after that, the signal recording was stopped
- The sequence of all the activities and locomotion for each session was as follows; START→STD→LW→RA→LW→SD→LW→SA→LW→RD→LW→STD→STOP
- Ten sessions (Ses1-Ses10) were recorded for each subject. Appropriate resting time was also provided in between the session as demanded by the subjects.

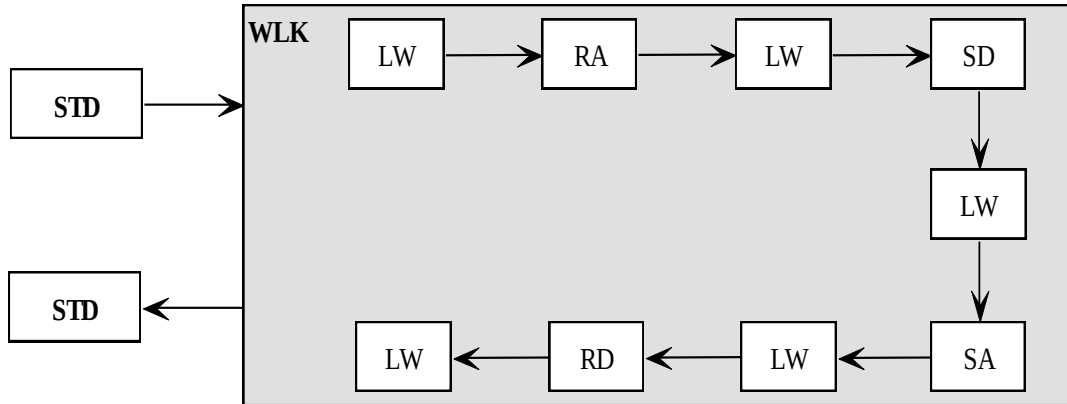


Figure 3.6 Activity sequences for experiment-2

This chapter describes the overall methodology followed in current research work for hybrid ankle-foot prosthesis development. It includes development of high-level and low-level controller to operate the prosthesis prototype. The high-level controller identifies the activity and locomotion intention of subject. Whereas, low-level controller estimates the ankle-foot angular position using EMG and KA signal. Two experiments have been designed to carry out the research work. During experiment-1, EMG signal of ten subjects have been acquired for weight bearing and non-weight bearing ankle-foot activities. In experiment-2, EMG signal, lower limb joint angle signal along with FSR foot sensor insole signal of ten subjects have been acquired for five daily life locomotion (LW, SA, SD, RA and RD). The dataset of experiment-1 have been used to select suitable below-knee muscles for ankle-foot movements and dataset of experiment-2 have been utilized to design activity/locomotion identification module and ankle joint estimation module.

Chapter 4

Muscle Selection and Locomotion Prediction

This chapter has two sections; the first section deals with the lower limb below-knee muscle selection suitable for ankle-foot movements, and the second section deals with the human activity and locomotion prediction. Section 4.1 describes the methodology, signal processing, and obtained results for lower limb below-knee muscle selection. The same has been presented for the activity and locomotion prediction module design in the subsequent part of the chapter, section 4.2.

4.1 Muscle Selection

In the human body, the CPG generates the basic motor pattern to achieve any limb movement. The generated motor pattern transmitted to the muscles through a complex biological structure as the EMG signal. Multiple muscles have been activated simultaneously to achieve any limb movement with particular force and torque [19]. It is not necessary to consider all muscles for prosthesis operation. The same movement at the prosthesis level can be achieved by a lesser number of muscles [134]. The prime movements of ankle-foot are DF and PF. Both of these ankle-foot movements are controlled by six superficial muscles, namely; Gast, Sole, TiAn, TiPo, PeBr, and PeLo [12]. Each muscle has different characteristics; hence their contribution also differs in limb movement. The redundancy of the musculoskeletal model can be improved by selecting the optimal set of muscles to provide suitable information regarding ankle joint movements. The muscle selection experiment is intended to select a set of below-knee muscles for PF/DF and PFW/DFW ankle-foot movements.

4.1.1 Methodology

Figure 4.1 shows the methodology opted for below-knee muscle selection for ankle-foot movements. The EMG signal of all six muscles has been compared on the basis of muscle activation duration, activation level, and fatigue level for repeated activity. Muscle activation duration and level have been estimated for all ankle-foot movements (PF, DF, PFW, and DFW). Whereas, for muscle fatigue assessment, only PFW and DFW activity have been considered.

Muscles depicting satisfactory performance for all three compared parameters have been considered for further analysis in current research work

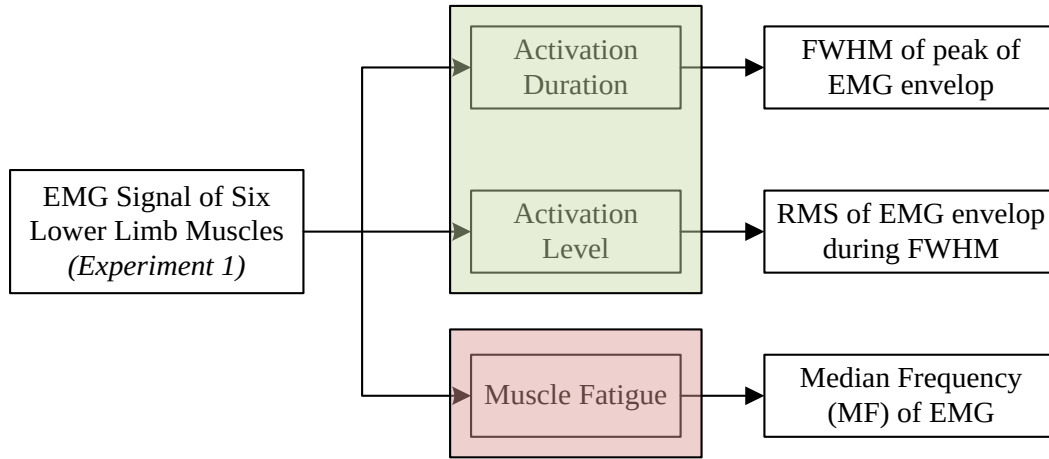


Figure 4.1 Methodology for muscle selection for ankle-foot movements

4.1.2 Signal Processing

Figure 4.2 shows the block diagram representation of steps followed for signal processing of the EMG signal. Each sample of EMG signal has been filtered through zero lag, 4th order Butterworth bandpass filter with a frequency range of 20-450 Hz followed by 50 Hz notch filter [135,136]. Further, the filtered EMG signal has been processed in two different ways; for muscle fatigue analysis and activation duration, activation level. For muscle fatigue analysis, the filtered EMG signal has been normalized using max-min normalization [137]. Whereas, for activation duration, activation level analysis, the filtered signal has been full-wave rectified using Eq. (4.1). After that, the envelope of the rectified EMG signal has been estimated by passing it through a zero lag, 2nd order Butterworth low-pass filter having cutoff frequency of 10 Hz [134]. The individual sample of the EMG envelop has been interpolated over time base with 1000 points using cubic spline interpolation technique [134]. Finally, the interpolated EMG envelop of each muscle has been normalized for individual activity using the max normalization technique [138–141].

$$EMG_{rect}(t) = \begin{cases} EMG(t) & \text{if } EMG(t) > 0 \\ -1 * EMG(t) & \text{if } EMG(t) \leq 0 \end{cases} \quad (4.1)$$

where, $EMG(t)$ is filtered EMG signal and, $EMG_{rect}(t)$ is a full-wave rectified EMG signal.

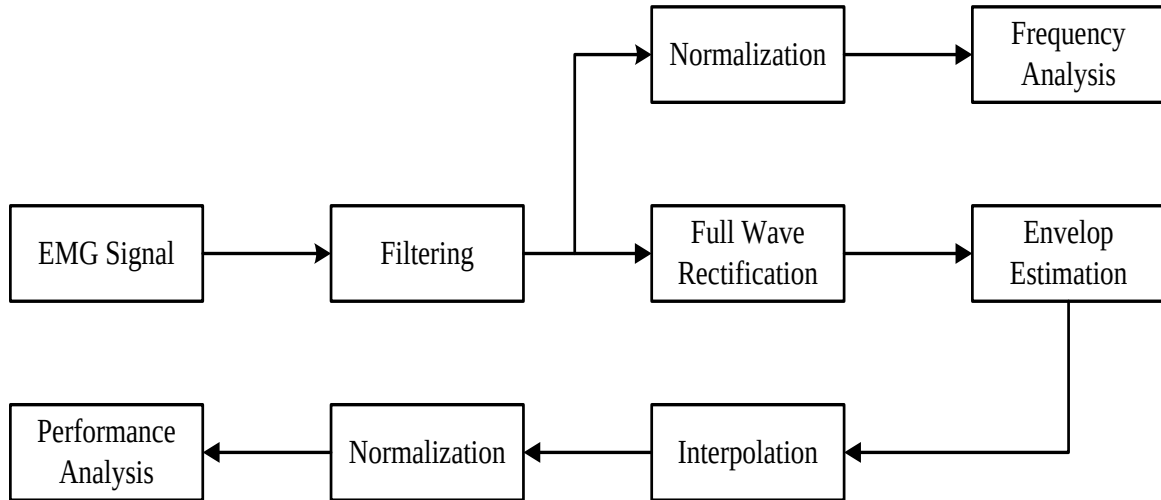


Figure 4.2 Signal processing steps for below-knee muscle selection

4.1.3 Performance Measures

The acquired EMG signal of both the phases of experiment-1 has been processed and analyzed separately for each subject. Dataset recorded during both the phases have been opted to access the consistency in the EMG signals for each activity of the subject. Whereas, for muscle fatigue analysis dataset of the only second phase of the experiment has been utilized. Any human limb movement or activity is performed by activating several muscles simultaneously. This activation of muscles is reflected as EMG signal. However, not all associated muscles will contribute in the same proportion for a particular activity. The muscle contributing higher will have a higher activation level (amplitude) as well as a larger activation duration. These parameters can be analyzed through EMG signal analysis. In the present research work, the muscle activation duration has been quantified by the Full Width at Half-Maximum (FWHM) of the main peak of normalized EMG envelop [140]. The FWHM is calculated as % of the activity duration and signifies the muscle activation duration w.r.to activity duration. The activation level of muscle has been evaluated as RMS of the normalized EMG envelope during FWHM. Figure 4.3 shows the pictorial representation of FWHM. For a particular activity, the muscle depicting higher FWHM indicates the higher activation duration and so as its higher contribution in that activity. In the same manner, the RMS value of FWHM indicates the amplitude or activation level of the muscle. Higher RMS value signifies the higher contribution of the muscle in a particular activity. Hence, both the parameters (FWHM and RMS) are directly proportional to the contribution made by the muscle during the activity. The fatigue of the muscle has been quantified as Median Frequency (MF) in

Hz. It has been considered a useful index for quantifying muscle fatigue during the dynamic condition. A degradation in MF signifies muscle fatigue and greater the reduction in MF higher muscle fatigue. The muscle having lower fatigue should be preferred over the other muscles [142].

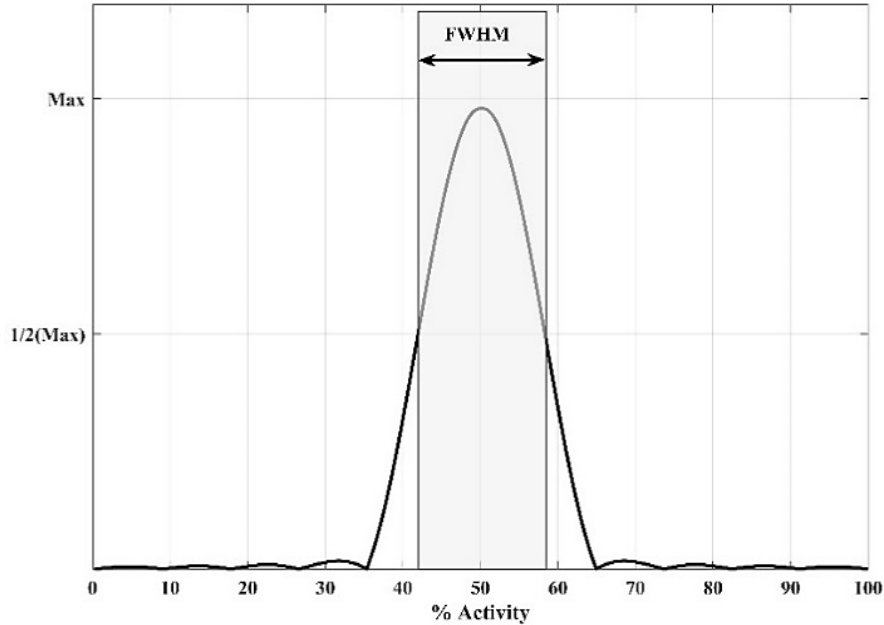


Figure 4.3 FWHM illustration

4.1.4 Results and Discussion

Table 4.1 shows the average FWHM over all subjects for individual muscle and activities. It is presented as % of the activity duration, as illustrated in Figure 4.3. It signifies the duration for which the muscle has been activated during the activity. During PF activity, Gast and Sole muscles show significantly higher FWHM ($47.45 \pm 3.50\%$ and $34.48 \pm 4.45\%$, respectively) as compared to other muscles. Whereas, for PFW activity TiAn, Gast, and Sole muscles show higher activity duration ($34.48 \pm 4.05\%$, $64.48 \pm 1.45\%$, and $52.47 \pm 6.24\%$, respectively) as compared to other muscles. TiAn is an additional muscle that activated during PFW activity as compared to PF activity. It provides additional support during weight bearing activity. It has been observed that the activation duration of Sole muscle for PF and PFW activity is inconsistent over the subjects as it carries the highest variation. In the case of DF and DFW activities, TiAn muscle shows significant activation duration ($57.24 \pm 1.48\%$ and $78.75 \pm 3.45\%$, respectively) as compared to other muscles. TiPo, PeBr, and PeLo muscles have shown insignificant participation in DF and DFW activities. However, their contribution has been found higher for weight bearing activities

(DFW and PFW) as compared to non-weight bearing activities (DF and PF). TiAn muscle has been found more reliable muscle for DF and DFW activities as it poses the lowest variation among all muscles. Similarly, for PF and PFW, Gast muscle has been found most reliable.

Table 4.1 Average FWHM (%) for all muscles and activities

Ankle Movements	Muscles					
	TiAn	Gast	Sole	TiPo	PeBr	PeLo
PF	5.15 $\pm$ 2.50	47.45 $\pm$ 3.50	34.48 $\pm$ 4.45	15.15 $\pm$ 2.35	5.18 $\pm$ 1.45	8.48 $\pm$ 2.57
DF	57.24 $\pm$ 1.48	12.17 $\pm$ 2.48	17.24 $\pm$ 3.54	12.48 $\pm$ 1.45	7.41 $\pm$ 3.42	7.47 $\pm$ 2.35
PFW	34.48 $\pm$ 4.05	64.48 $\pm$ 1.45	52.47 $\pm$ 6.24	18.41 $\pm$ 2.47	14.37 $\pm$ 4.12	10.41 $\pm$ 3.48
DFW	78.75 $\pm$ 3.45	34.72 $\pm$ 4.58	34.65 $\pm$ 4.02	20.45 $\pm$ 3.04	15.89 $\pm$ 4.25	11.14 $\pm$ 4.05

Table 4.2 shows the average RMS value during the FWHM for all muscles and activities. It signifies the activation level/contribution of the muscle during the activity. All muscles show higher activation level for weight bearing activities (PFW and DFW) as compared to non-weight bearing activities (PF and DF). For PF activity, Gast and Sole muscles show the higher RMS value (0.60 ± 0.022 and 0.58 ± 0.031 , respectively) as compare to other muscles while PF activity. Further, the Gast muscle has been found more reliable over Sole muscle as it shows lesser variation. Similar results have been found for PFW activates where Gast and Sole muscles outperformed over all other muscles with RMS value as 0.87 ± 0.044 and 0.75 ± 0.094 , respectively. During DF and DFW activities, TiAn muscle contributed the most as compared to other muscles with RMS value of 0.54 ± 0.02 and 0.84 ± 0.082 , respectively. Also, its response has been found more reliable as compared to other muscles.

Table 4.2 Average RMS during the FWHM for all muscles and activities

Ankle Movements	Muscles					
	TiAn	Gast	Sole	TiPo	PeBr	PeLo
PF	0.14 $\pm$ 0.019	0.60 $\pm$ 0.022	0.58 $\pm$ 0.031	0.24 $\pm$ 0.094	0.20 $\pm$ 0.047	0.31 $\pm$ 0.034
DF	0.54 $\pm$ 0.025	0.18 $\pm$ 0.035	0.12 $\pm$ 0.042	0.15 $\pm$ 0.042	0.14 $\pm$ 0.087	0.17 $\pm$ 0.054
PFW	0.25 $\pm$ 0.067	0.87 $\pm$ 0.044	0.75 $\pm$ 0.094	0.26 $\pm$ 0.052	0.52 $\pm$ 0.042	0.48 $\pm$ 0.068
DFW	0.84 $\pm$ 0.082	0.30 $\pm$ 0.048	0.35 $\pm$ 0.078	0.47 $\pm$ 0.087	0.27 $\pm$ 0.029	0.31 $\pm$ 0.078

Figure 4.4 shows the average MF for each muscle. It has been estimated over the different number of activity repetitions to analyze the fatigue level of muscle. The reduction in MF over activity repetitions signifies the level of fatigue of the particular muscle. The results show a decline of 53%, 48%, and 33% in MF for TiPo, PeBr, and PeLo activities, respectively. TiAn and Gast muscles show the least decrement in MF as 14% and 13%. TiAn and Gast muscles came out as least fatigued muscles for weight bearing activities. The common muscles performing superior in all three compared parameters (activation level, activation duration, and muscle fatigue) are selected for further analysis. TiAn and Gast muscles have been found top-performing muscles over compared to parameters. Hence, TiAn and Gast muscles are selected for further analysis of ankle-foot movements.

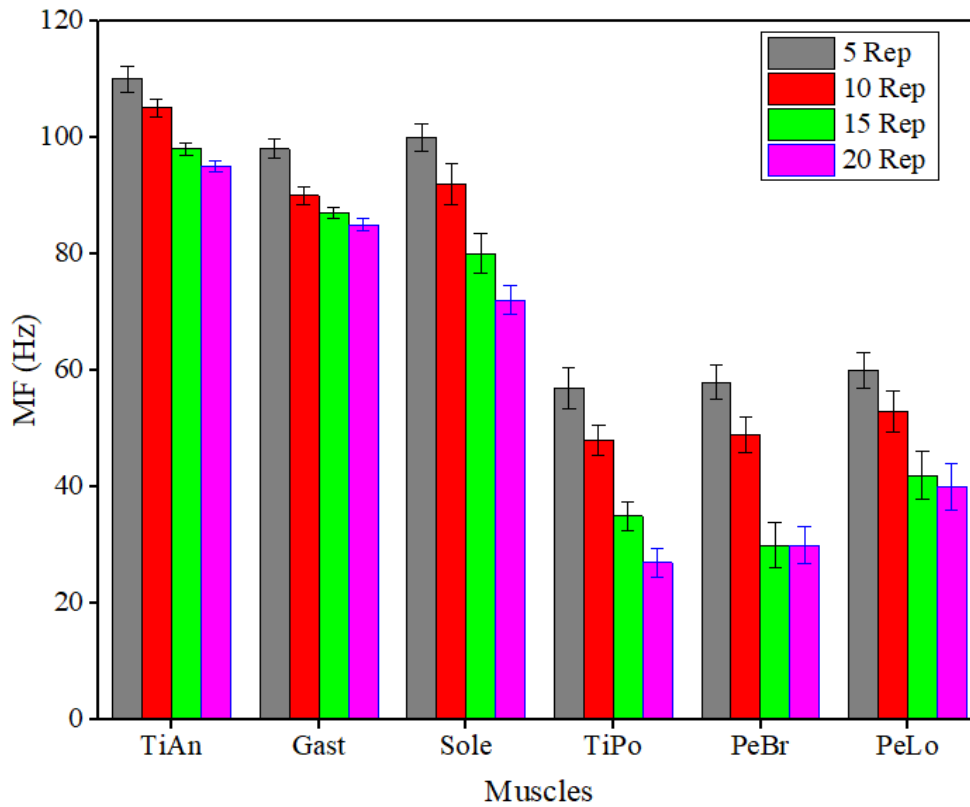


Figure 4.4 Average MF of each muscle for weight bearing activities

4.2 Activity and Locomotion Prediction

Activity and locomotion prediction module act as a high-level controller for prosthesis control. It detects the locomotion and activity intention of the subject and offers seamless operation of the prosthesis.

4.2.1 Methodology

The current research work utilized a two-level classification approach for activity and locomotion prediction. It operates sequentially in two levels, as shown in Figure 4.5. At the first level, the activity of the subject between STD and WLK has been identified. If the subject is walking, then only its type of locomotion has been predicted at the second level of classification. Five steady-state locomotion (LW, SA, SD, RA, and RD) and nine locomotion transitions (LW↔SA/SD, LW↔RA/RD, and LW→STD) have been considered.

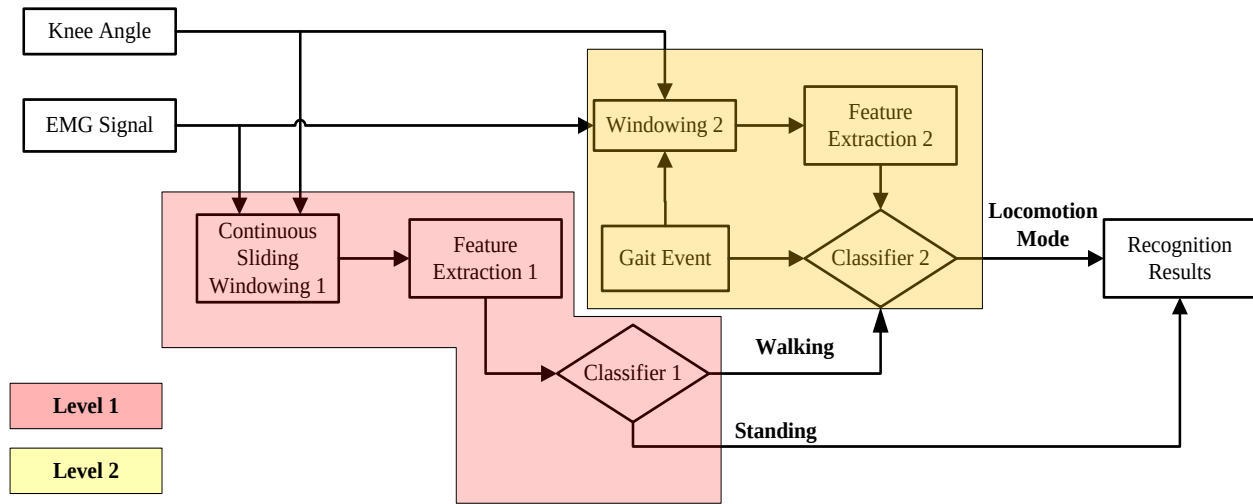


Figure 4.5 Methodology for activity and locomotion prediction

Figure 4.6 shows the major steps followed for the activity/locomotion prediction. It will predict the subsequent locomotion before the critical event so that the required control signal can be generated. It results in the seamless operation of the prosthesis without any cognitive effort of the subject. It utilizes the EMG signal of lower limb muscles and KA to predict locomotion. The KA signal provides existing knee joint orientation, whereas EMG signals precede movement onset and will be very useful to predict locomotion [88]. The stability of the EMG signal is always a matter of concern for the researchers. It has an adverse effect on the performance of the system. On the other hand, the KA signal is more stable. Hence, for the current research, the KA signal is combined with the EMG signal for locomotion and activity prediction. The major steps for the activity/locomotion prediction include signal processing, feature extraction, and classification. All the aforementioned steps are discussed in subsequent sections.

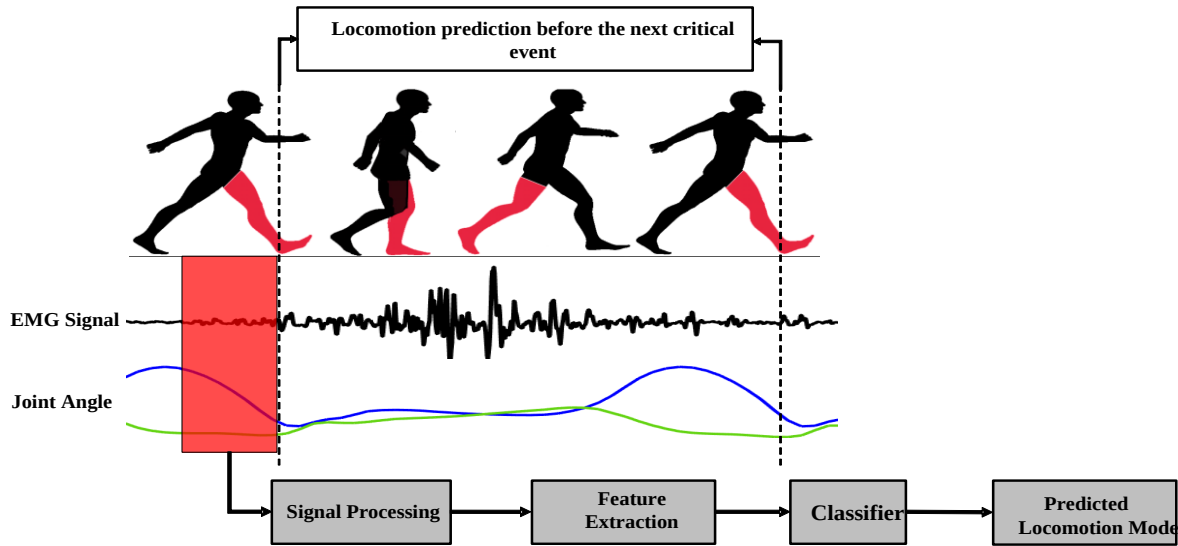


Figure 4.6 General steps for activity/locomotion prediction

4.2.2 Signal Processing, Features and Classifiers

4.2.2.1 Signal Processing

The conventional classification approach applied for upper limb prosthesis control can be used to predict locomotion mode with some modifications because, within the same locomotion mode, the EMG signal pattern changes with time. It shows the lesser variation in a short time window. So, signal processing has been applied in a short time window of the signal. At level-1 classification, it is necessary to put a continuous check on the signal to check whether the subject is standing or walking. Hence, for level-1 classification, a continuous overlapped windowing technique has been applied, as shown in Figure 4.7. The length of window size and window shift has been kept 256 msec and 32 msec, respectively [135]. In level-2 classification, a gait phase-dependent multi classifier approach has been implemented for locomotion prediction.

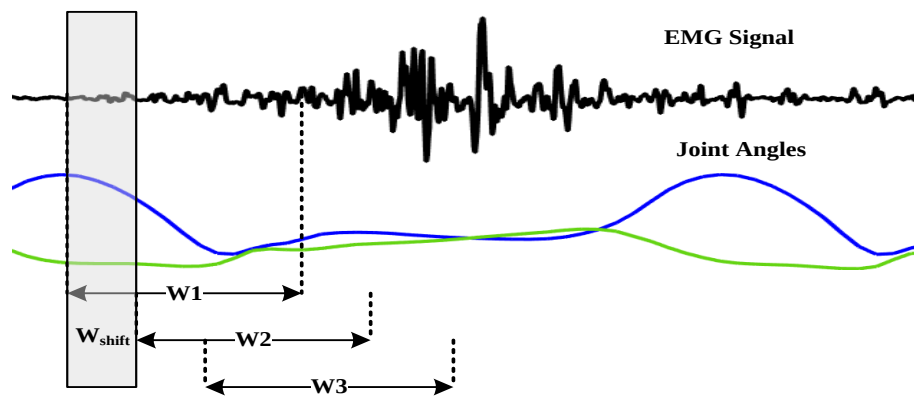


Figure 4.7 Continuous overlapped windowing for level-1 classification

Figure 4.8 shows the internal architecture of the locomotion prediction module (level-2 classification). The multichannel EMG and KA signals have been simultaneously streamed into this system and, then, segmented into subwindows as per the gait events. In each subwindow, features of EMG and KA signal have been extracted. After that, both EMG features and KA features have been fused into one feature vector for each subwindow. This feature vector has been sent to a gait phase-dependent classifier, which deals with the nonstationary nature of EMG signals efficiently. This gait phase-dependent classifier has multiple classifiers and each of which utilizes feature vector of respective gait subwindow. The FSR foot sensor insole determines the current gait phase and switches on the corresponding classifier. Further, the respective classifier decides the locomotion mode based on the input feature vector.

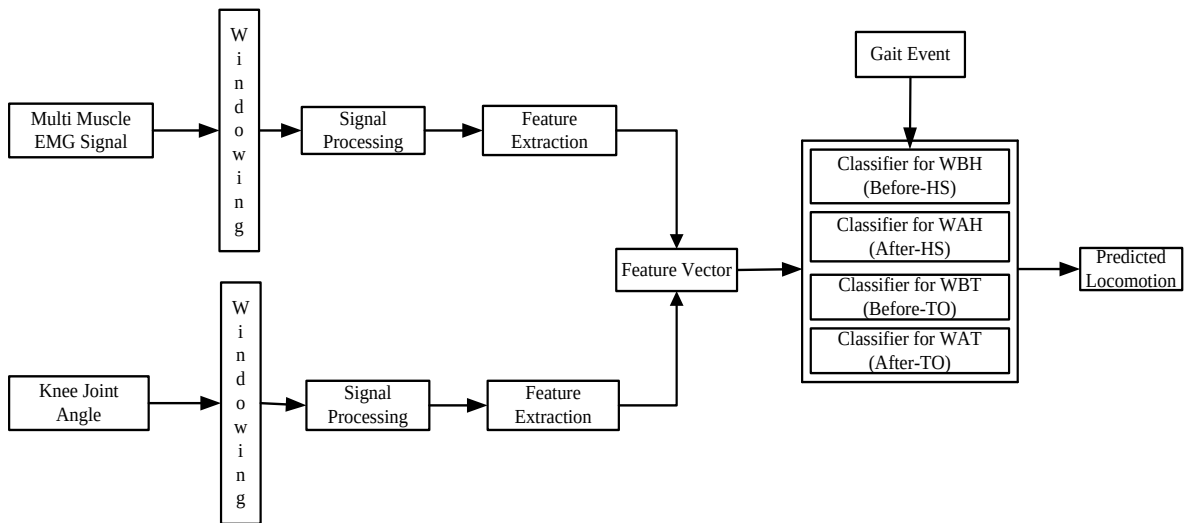


Figure 4.8 Architecture of locomotion prediction module (level-2)

Four subwindows over a complete gait cycle have been extracted, and for each subwindow, an individual classifier has been designed, as shown in Figure 4.9. The subwindows have been extracted before and after of the HS and TO gait event, namely; Window After Heel-Strike (WAH), Window Before Toe-Off (WBT), Window After Toe-Off (WAT) and Window Before Heel-Strike (WBH). The subwindow size has been selected by comparing the performance of various subwindow size. The size of subwindows has been varied between 50 msec to 300 msec with an increment of 50 msec. Hence, six subwindow sizes have been compared. Different signal processing steps have been followed for EMG and KA signal. Also, a different set of features have been calculated for EMG and KA signal. Further, the feature vector for each window has been constituted by concatenating all the features and current activity/locomotion.

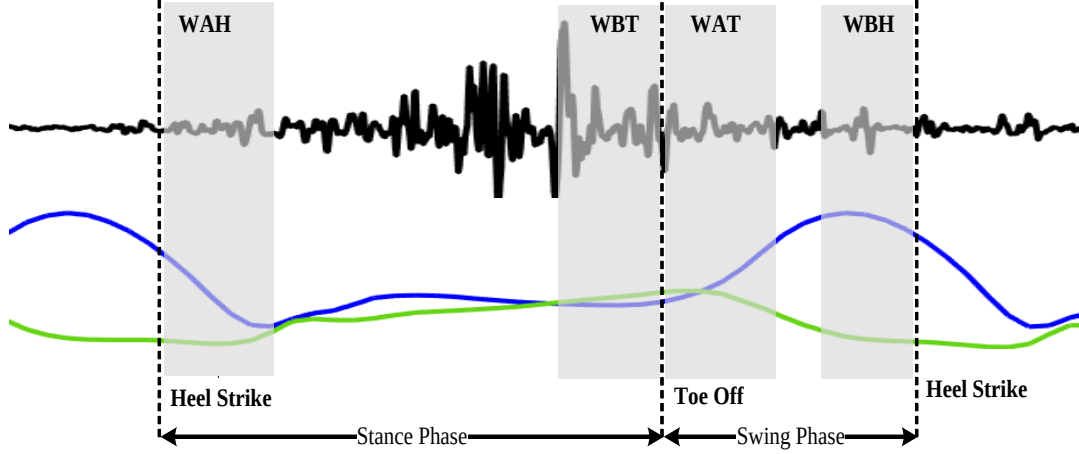


Figure 4.9 Subwindows of signals for one complete gait cycle (level-2)

EMG and KA signals are very different from each other. Hence, different signal processing has been applied to both signals. First of all, both the signals have been segmented as per their window size for level-1 and level-2, respectively. Thereafter, the EMG signal has been filtered using the 4th order zero-lag bandpass Butterworth filter with the frequency band of 10-450 Hz followed by a 50 Hz notch filter to remove the power line interference. Whereas, the KA signal has been filtered using a low-pass filter to trim out the high-frequency noise. A 2nd order, zero-lag Butterworth low-pass filter of 10 Hz cut off frequency, has been applied to the KA signal [143].

4.2.2.2 Features and Feature Vector

Feature selection plays a vital role in prediction model performance [144–146]. Features have been extracted for the individual window of EMG and KA signal. In Level-1 classification, Mean Absolute Value (MAV) of the EMG signal and the average value of the KA signal has been extracted for each window. Whereas, for level-2 classification, total thirty-eight features of EMG signals have been extracted. Table 4.3 presents the name and mathematical definition of all the extracted features [137]. Here, an iterative classifier-dependent weighted accuracy feature selection algorithm has been applied to select the optimal set of features for EMG signal [136]. Four features (maximum, minimum, average, and variance) of the KA signal for each segmented window has been estimated and used as features. In both levels (1 and 2) of classification, the individual feature has been normalized for every subject using the min-max normalization method as given by Eq. (4.2) [137].

$$F_{norm} = \frac{F - \min(F)}{\max(F) - \min(F)} \quad (4.2)$$

where F_{norm} is normalized feature value, F is the actual feature value, $\min(F)$, and $\max(F)$ are minimum and maximum value of the feature respectively over all trials. The feature vectors have been constructed for each segmented window by concatenating normalized features of EMG signal and KA.

Table 4.3 Name and definition of extracted features

S. No.	Abv.	Feature Name	Definition
1	IEMG	Integrated EMG	$IEMG = \sum_{i=1}^N X_i $
2	MAV	Mean absolute value	$MAV = \frac{1}{N} \sum_{i=1}^N X_i $
3	MAV1	Modified mean absolute value type 1	$MAV1 = \frac{1}{N} \sum_{i=1}^N w_i X_i $ $w_i = \begin{cases} 1 & \text{if } 0.25N \leq i \leq 0.75N \\ 0.5 & \text{otherwise} \end{cases}$
4	MAV2	Modified mean absolute value type 2	$MAV2 = \frac{1}{N} \sum_{i=1}^N w_i X_i $ $w_i = \begin{cases} 1 & \text{if } 0.25N \leq i \leq 0.75N \\ \frac{4i}{N} & \text{elseif } i < 0.25N \\ \frac{4(i-N)}{N} & \text{otherwise} \end{cases}$
5	SSI	Simple square integral	$SSI = \sum_{i=1}^N X_i^2$
6	VAR	Variance of EMG	$VAR = \frac{1}{N-1} \sum_{i=1}^N X_i^2$
7	TM3	Absolute value of the 3 rd temporal moment	$TM3 = \left \frac{1}{N} \sum_{i=1}^N X_i^3 \right $
8	TM4	Absolute value of the 4 th temporal moment	$TM4 = \left \frac{1}{N} \sum_{i=1}^N X_i^4 \right $

9	TM5	Absolute value of the 5 th temporal moment	$TM5 = \left \frac{1}{N} \sum_{i=1}^N X_i^5 \right $
10	RMS	Root mean square	$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^N X_i^2}$
11	LOG	Log detector	$LOG = e^{\frac{1}{N} \sum_{i=1}^N \log(X_i)}$
12	WL	Waveform length	$WL = \sum_{i=1}^{N-1} X_{i+1} - X_i $
13	AAC	Average amplitude change	$AAC = \frac{1}{N} \sum_{i=1}^{N-1} X_{i+1} - X_i $
14	DASDV	Difference absolute standard deviation value	$DASDV = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} (X_{i+1} - X_i)^2}$
15	ZC	Zero crossing	$ZC = \sum_{i=1}^{N-1} [sgn(X_i \times X_{i+1}) \cap X_i - X_{i+1} \geq threshold]$ $sgn(X) = \begin{cases} 1, & \text{if } X \geq thrsehold \\ 0, & \text{otherwise} \end{cases}$
16	MYOP	Myopulse percentage rate	$MYOP = \frac{1}{N} \sum_{i=1}^N [f(X_i)]$ $f(X) = \begin{cases} 1, & \text{if } X \geq threshold \\ 0, & \text{otherwise} \end{cases}$
17	WAMP	Willison amplitude	$WAMP = \sum_{i=1}^{N-1} [f(X_n - X_{n+1})]$ $f(X) = \begin{cases} 1, & \text{if } X \geq threshold \\ 0, & \text{otherwise} \end{cases}$
18	SSC	Slope sign change	$SSC = \sum_{i=2}^{N-1} [f[(X_i - X_{i-1}) \times (X_i - X_{i+1})]]$ $f(X) = \begin{cases} 1, & \text{if } X \geq threshold \\ 0, & \text{otherwise} \end{cases}$
19	H1	Histogram of EMG	Histogram of EMG
20	H2		
21	H3		
22	H4		
23	H5		

24	MNF	Mean frequency	$MNF = \frac{\sum_{j=1}^M f_j P_j}{\sum_{j=1}^M P_j}$
25	MDF	Median frequency	$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^M P_j = \frac{1}{2} \sum_{j=1}^M P_j$
26	PKF	Peak frequency	$PKF = \max(P_j), j = 1, 2, \dots, M$
27	MNP	Mean power	$MNP = \frac{\sum_{j=1}^M P_j}{M}$
28	TTP	Total power	$TTP = \sum_{j=1}^M P_j = SM0$
29	SM1	1 st Spectral moment	$SM1 = \sum_{j=1}^M P_j f_j$
30	SM2	2 nd Spectral moment	$SM2 = \sum_{j=1}^M P_j f_j^2$
31	SM3	3 rd Spectral moment	$SM3 = \sum_{j=1}^M P_j f_j^3$
32	FR	Frequency ratio	$FR = \frac{\sum_{j=LL}^{UL} P_j}{\sum_{j=LH}^{UH} P_j}$
33	PSR	Power spectrum ratio	$PSR = \frac{P_0}{P} = \frac{\sum_{j=f_0-n}^{f_0+n} P_j}{\sum_{j=-\infty}^{\infty} P_j}$
34	VCF	Variance of central frequency	$VCF = \frac{1}{SM0} \sum_{j=1}^M P_j (f_j - f_c)^2 = \frac{SM2}{SM0} - \left(\frac{SM1}{SM0}\right)^2$
35	AR1	Auto-regressive coefficients	$X_i = \sum_{p=1}^p a_p X_{i-p} + w_i$ p is the order of the AR model, w_i is the white noise error term
36	AR2		
37	AR3		
38	AR4		

Time-domain Features

Frequency-domain Features

Predictive Features

Note: where X_i represents the EMG signal in a segment i and N denotes the length of EMG signal, f_j is the frequency of the spectrum at frequency bin j , P_j is the EMG power spectrum at frequency bin j and M is the length of the frequency bin. UL, LL: upper and lower cut-off frequency of lower frequency band UH, LH: upper and lower cut-off frequency of upper frequency band

4.2.2.3 *Classifiers*

The classifier is defined as a function of input values in the form of feature vectors and predicts the class they belong to. The selection of appropriate classifier for an application is one of the critical factors for efficient performance. However, a classifier should be able to provide satisfactory performance with minimum training data and computationally efficient for its real-time implementation. Here, for both levels (1 and 2) of classification, the performance of linear and non-linear classifiers has been compared. LDA classifier is chosen as a linear classifier, and SVM with nonlinear kernel and NN are chosen as the non-linear classifier. The compared classifiers are LDA, SVM, and NN, these classifiers had shown promising performance in the past for a variety of biomedical applications [65,128,145,147–149]. LDA is one of the most widely and commonly used classifiers for EMG signal-based pattern recognition problems. Its classification performance has been found comparable to most of the complex classifiers. Moreover, being computationally efficient, it is best suited for biomedical and myoelectric prosthesis control [150].

The SVM classifier is a relatively new classification technique. It belongs to the family of kernel-based classifiers. It implicitly maps the data into the feature space where a decision boundary separates the classes. If data is linear, a linear kernel separating hyperplane is used to classify the data and known as linear SVM. Further, for the classification of non-linear and high transitional data, the formulation of linear hyperplane is extended to build non-linear SVM kernel. Non-linear kernel transforms the input data into the feature space of higher dimensions [150]. In this research work, a one versus one SVM classifier with quadric kernel has been utilized.

NN is a more complex classifier as compared to LDA and SVM classifiers. Various researchers have repeatedly used it for EMG signal-based pattern recognition problems. It uses a recursive training method to generate nonlinear boundaries among classes for the classification of feature vectors [150]. In the present research work, a fully connected two-layer NN classifier with ten neurons in the hidden layer has been developed. The network has been trained using the backpropagation training algorithm keeping MSE as a performance measure. To avoid overfitting, the validation test was used to stop training iterations. The momentum parameter and learning rate has been kept as 0.6 and 0.05, respectively.

4.2.3 Performance Evaluation

4.2.3.1 Feature Selection of EMG Signal for Level-2 Classification

A total of thirty-eight features of EMG signal have been extracted for locomotion mode prediction in addition to KA features. To select an optimal set of EMG signal features, an iterative classifier-dependent weighted accuracy feature selection algorithm has been implemented. Steady-state locomotion samples have been considered for EMG signal feature selection. The applied feature selection technique is a classifier dependent algorithm. It is applied and tested for all three classifiers and muscles individually. Before applying the feature selection algorithm, the EMG signal of lower limb muscles has been preprocessed using 4th order, zero lag, Butterworth bandpass filter of frequency 10-450 Hz followed by 50 Hz notch filter. Afterward, signal segmentation has been done through overlapped windowing with window length and shift of 256 msec and 32 msec, respectively [135]. The features for each window have been estimated, and the individual feature has been normalized using the min-max normalization method. The feature vector corresponding to each window segment acted as a sample of the training set. An optimal set of EMG features have been estimated for all individual muscle and classifier using feature selection algorithm, and at last, the common set of features for all classifiers has been estimated and utilized further for locomotion prediction besides with KA signal.

4.2.3.2 Subwindow Size and Muscle Group Selection for Level-2 Classification

The subwindow size around the gait events affects the performance of the classifier. The EMG signal is often modeled as a Gaussian random process. A short analysis window contains very high variance in estimated features, whereas if the size of the analysis window increases, the variation in estimated features reduces. It provides higher classification accuracy but at the cost of higher delay in the system. The literature suggests that the delay in myoelectric control system should be within 300 msec. The current research work compares the performance of the prediction model for the six different window sizes ranging from 50 msec to 300 msec, with an increment of 50 msec shown in Table 4.4.

Table 4.4 Compared subwindow sizes for level-2 classification

Subwindows	W1	W2	W3	W4	W5	W6
Subwindow sizes	50 msec	100 msec	150 msec	200 msec	250 msec	300 msec

The muscle group selection deals with the muscle combinations suitable for locomotion prediction along with KA information. Each muscle contributes differently to human biomechanics. A total of six lower limb muscles have been considered for the current research work, which includes two below-knee (TiAn and Gast) and four above-knee muscles (VaLa, ReFe, Semd, and BiFe). The performance of classifiers has been evaluated for various groups of muscles comprising of two, three, four, five, and six muscles in addition to the KA signal. Table 4.5 shows the various muscle combinations compared to locomotion predication. The performance of all three classifiers (LDA, SVM, and NN) have been evaluated for all possible combinations of window sizes and muscle groups. Here, Leave One Out Cross Validation (LOOCV) scheme has been used for performance analysis. In LOOCV, out of a total of ten trails of collected data of each subject, data of nine trials have been used for training of the classifier, and one trail was used to estimate the testing classification accuracy. This procedure keeps on repeating until each trail has been used once as the testing data. LOOCV classification accuracy of steady-state locomotion predication has been used as performance measures of classifiers.

Table 4.5 Various muscle combinations for level-2 classification

No. of muscles in a group	Muscles in groups
Two (G1-G12)	(TiAn, VaLa), (TiAn, ReFe), (TiAn, Semd), (TiAn, BiFe), (Gast, VaLa), (Gast, ReFe), (Gast, Semd), (Gast, BiFe), (VaLa, Semd), (VaLa, BiFe), (ReFe, Semd), (ReFe, BiFe)
Three (G13-G16)	(TiAn, Gast, VaLa), (TiAn, Gast, ReFe), (TiAn, Gast, Semd), (TiAn, Gast, BiFe)
Four (G17-G22)	(TiAn, Gast, ReFe, Semd), (TiAn, Gast, VaLa, ReFe), (TiAn, Gast, VaLa, Semd), (TiAn, Gast, ReFe, BiFe), (TiAn, Gast, Semd, BiFe), (TiAn, Gast, VaLa, BiFe)
Five (G23-G26)	(TiAn, Gast, ReFe, Semd, BiFe), (TiAn, Gast, VaLa, ReFe, Semd), (TiAn, Gast, VaLa, Semd, BiFe), (TiAn, Gast, VaLa, ReFe, BiFe)
Six (G27)	(TiAn, Gast, VaLa, ReFe, Semd, BiFe)

4.2.3.3 Classifier Performance

The performance of the classifiers, at both levels (1 and 2) of classifications, have been evaluated by using the LOOCV scheme. For level-1 classification, the performance of the classifier has been quantified as the overall % classification accuracy using Eq. (4.3), following the LOOCV scheme.

$$\%Acc_{SS} = \frac{\text{No. of correctly classified testing sampels}}{\text{Total no. of applied testing samples}} \times 100 \quad (4.3)$$

The performance of the prediction model for level-2 classification has been estimated for steady-state locomotion mode classification and locomotion mode transitions separately. Overall % classification accuracy has been used as a performance index to quantify the classifier performance for steady-state locomotion classification, shown as Eq. (4.3). In addition to the % classification accuracy, the Confusion Matrix (CM), as Eq. (4.4), has also been computed depicting the relationship between the actual locomotion mode and the predicted locomotion mode.

$$CM = \begin{pmatrix} C_{11} & C_{12} & \dots & \dots & C_{1m} \\ \dots & C_{22} & \dots & \dots & \dots \\ \dots & \dots & C_{33} & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ C_{m1} & C_{m2} & \dots & \dots & C_{mm} \end{pmatrix} \quad (4.4)$$

The m represents the number of locomotion modes, i.e., 5. The element C_{ij} in matrix CM is defined as Eq. (4.5).

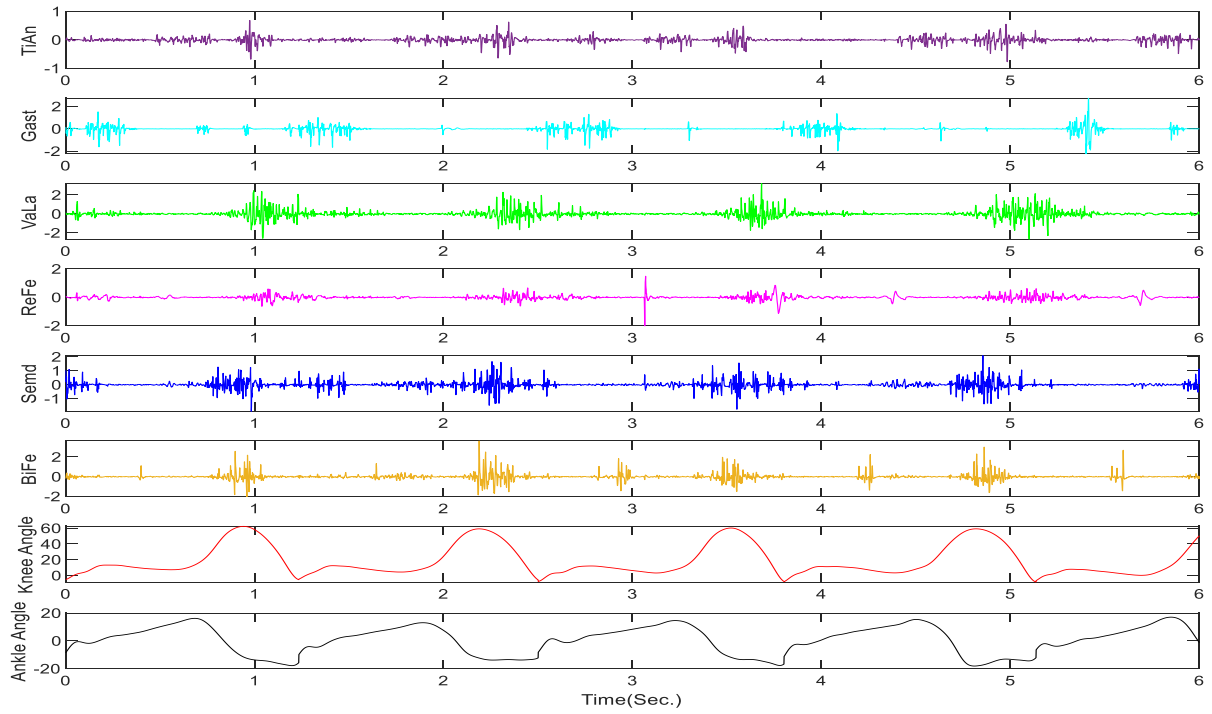
$$C_{ij} = \frac{\text{No. of testing data of class } i \text{ predicted as class } j}{\text{Total no. of testing data in class } j} \times 100 \quad (4.5)$$

The performance of the prediction model for locomotion mode transitions has been accessed by evaluating the % of incorrectly predicted transitions, using Eq.(4.6) for a particular transition. The performance of the prediction model has been estimated for each subject individually.

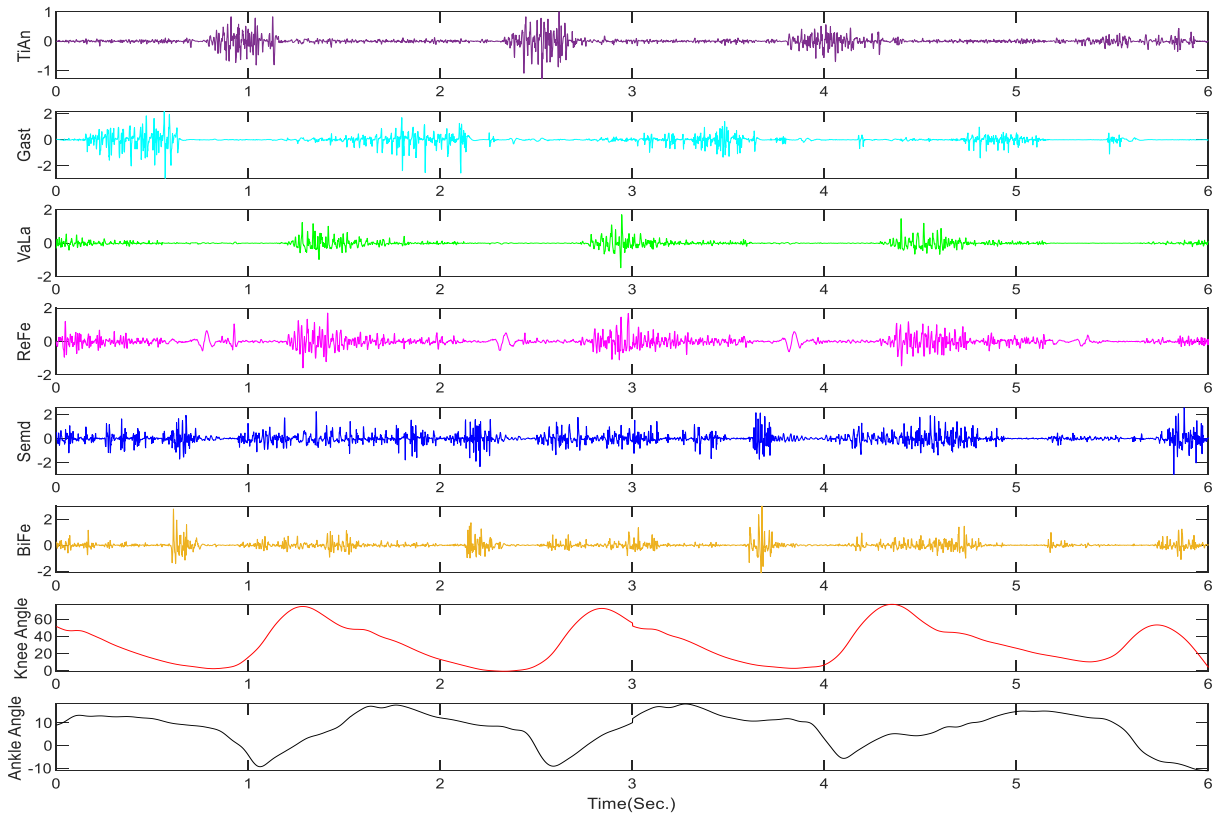
$$\%Err_{Tr} = \frac{\text{No. of incorrect identified transitions in testing data}}{\text{Total no. of transitions in testing data}} \times 100 \quad (4.6)$$

4.2.4 Results and Discussion

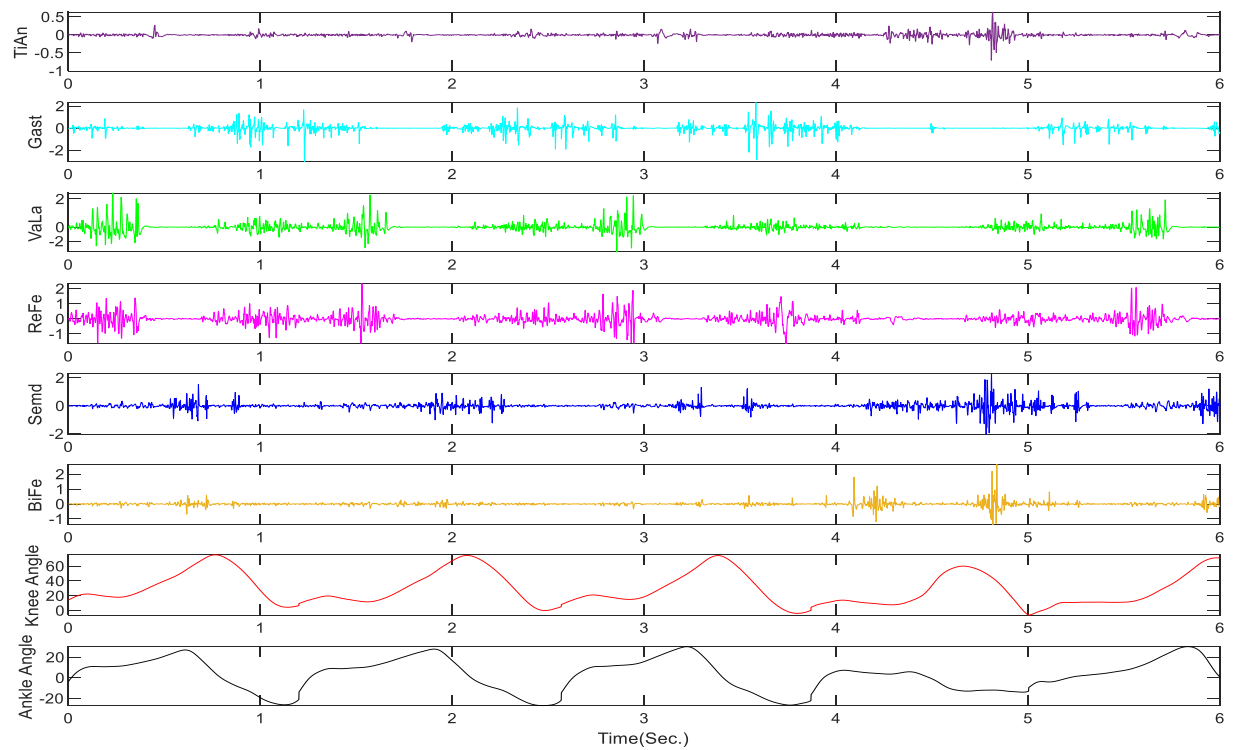
Figure 4.10 shows the recorded EMG and KA signal for each locomotion during experiment-2.



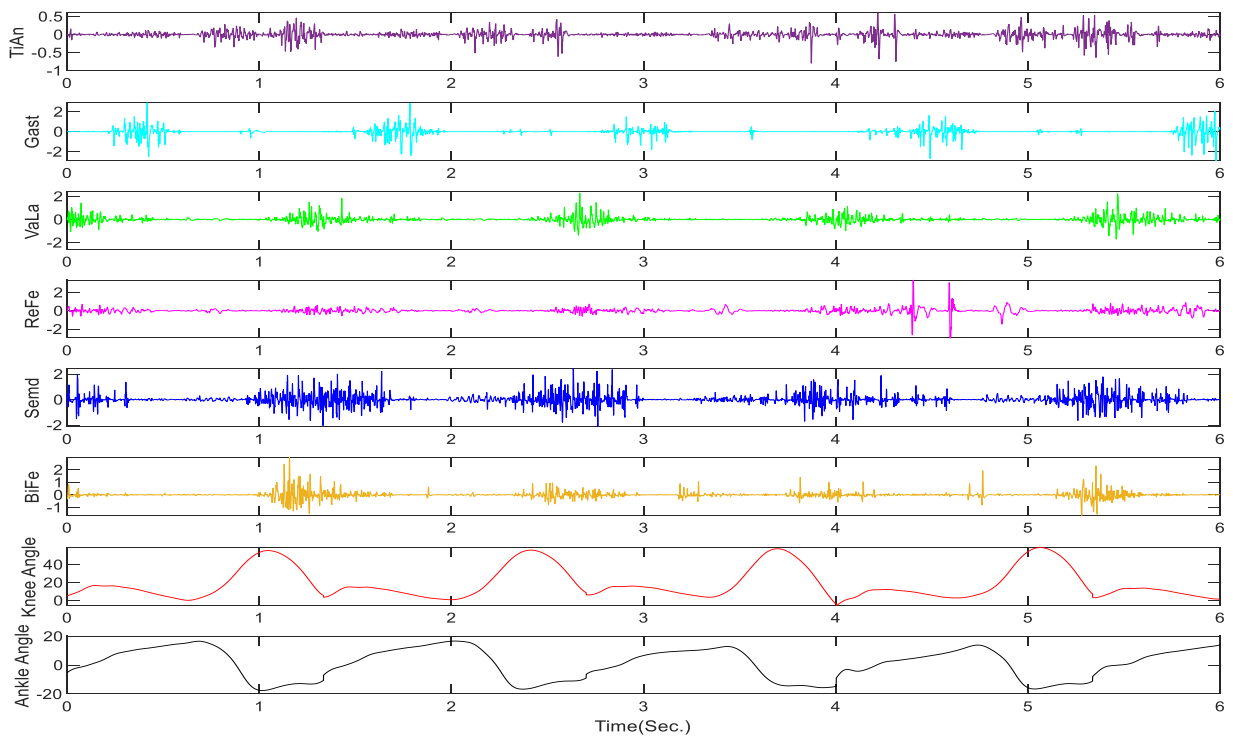
(a) LW



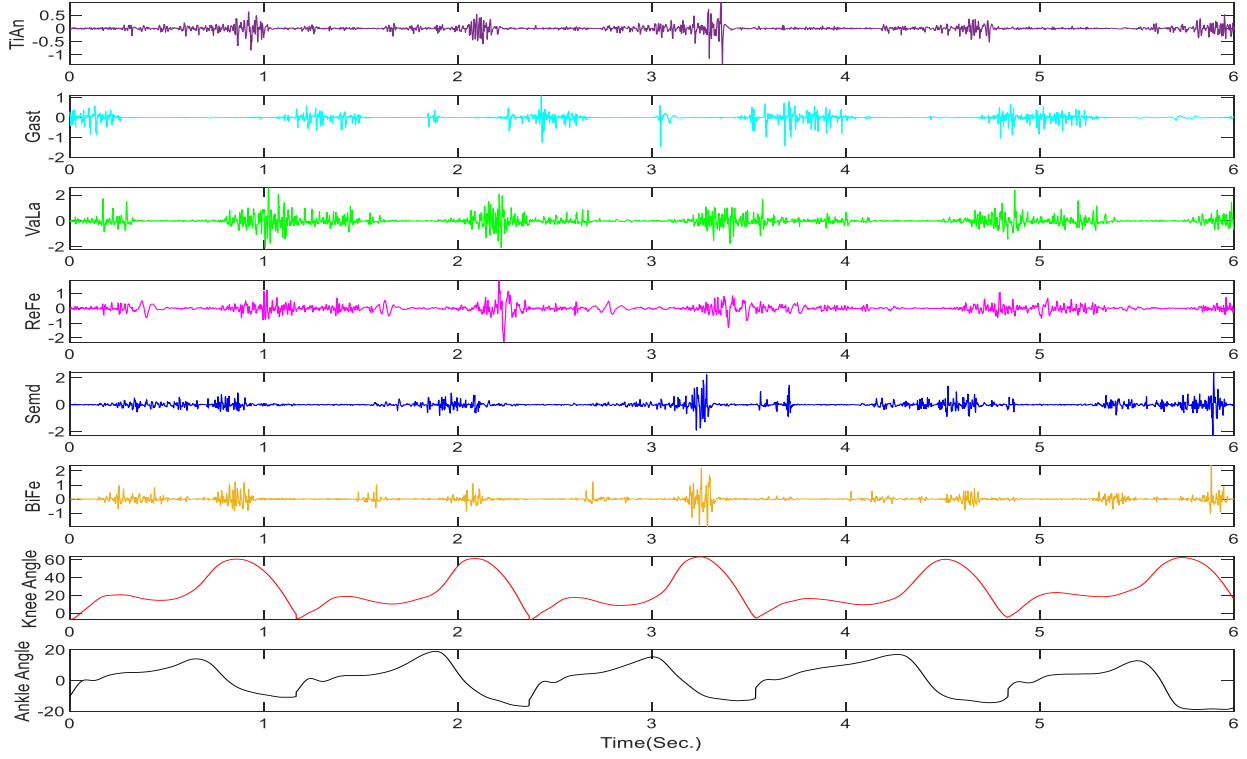
(b) SA



(c) SD



(d) RA



(e) RD

Figure 4.10 Illustration of EMG and lower limb joint angles for different locomotion

4.2.4.1 Performance for level-1 classification

Level-1 classification deals with human activity identification between STD and WLK. It is a two-class classification problem. It utilizes EMG signals of four lower limb muscles (TiAn, Gast, VaLa, and BiFe) and the KA signal. One feature corresponding to each signal has been calculated to constitute the feature vector. MAV of the EMG signal of each muscle and the average value of the KA signal has been used as a feature. Hence, the dimension of the feature vector becomes five, *i.e.*, four features corresponding to the EMG signal of each muscle and one feature corresponding to the KA signal.

Table 4.6 shows the performance of all three classifiers (LDA, SVM, and NN) for all subjects. All classifiers show a classification accuracy of more than 98% for all subjects. Moreover, the One-way ANOVA analysis shows no statistically significant difference in classification accuracy among subjects ($p\text{-value} > 0.05$), *i.e.*, each classifier performs equally well for all subjects. Figure 4.11 depicts the average performance of all the classifiers using only knee angle information alone and hybrid (KA+EMG) information. The average % classification accuracy shown by LDA, SVM, and NN classifiers is 98.56 ± 0.99 , 98.54 ± 1.05 , and $98.39 \pm 1.19\%$, respectively (One-way

ANOVA, $p\text{-value} > 0.05$) while using hybrid (KA+EMG) information. Whereas, for only KA information alone, it has been found as 80.76 ± 1.34 , 77.43 ± 1.38 , and $77.92 \pm 1.23\%$ for LDA, SVM and NN classifier, respectively (One-way ANOVA, $p\text{-value} < 0.05$). All the classifiers have shown considerably good performance with hybrid (EMG+KA) information.

Table 4.6 % classification accuracy of various classifiers for level-1 classification

Subject	Classifiers		
	LDA	SVM	NN
S1E2	98.34 ± 0.94	98.87 ± 1.00	98.38 ± 1.21
S2E2	98.67 ± 0.99	98.97 ± 1.05	98.91 ± 1.24
S3E2	98.65 ± 1.00	98.39 ± 1.08	98.39 ± 0.98
S4E2	98.43 ± 1.01	98.79 ± 1.11	98.62 ± 1.19
S5E2	98.29 ± 0.90	98.47 ± 1.13	98.33 ± 1.25
S6E2	98.88 ± 0.92	98.16 ± 1.05	98.47 ± 1.33
S7E2	98.10 ± 1.07	98.18 ± 0.98	98.39 ± 0.96
S8E2	98.30 ± 1.01	98.58 ± 1.01	98.13 ± 1.27
S9E2	99.10 ± 1.12	98.56 ± 1.00	98.28 ± 1.24
S10E2	98.90 ± 0.96	99.05 ± 1.17	98.01 ± 1.31

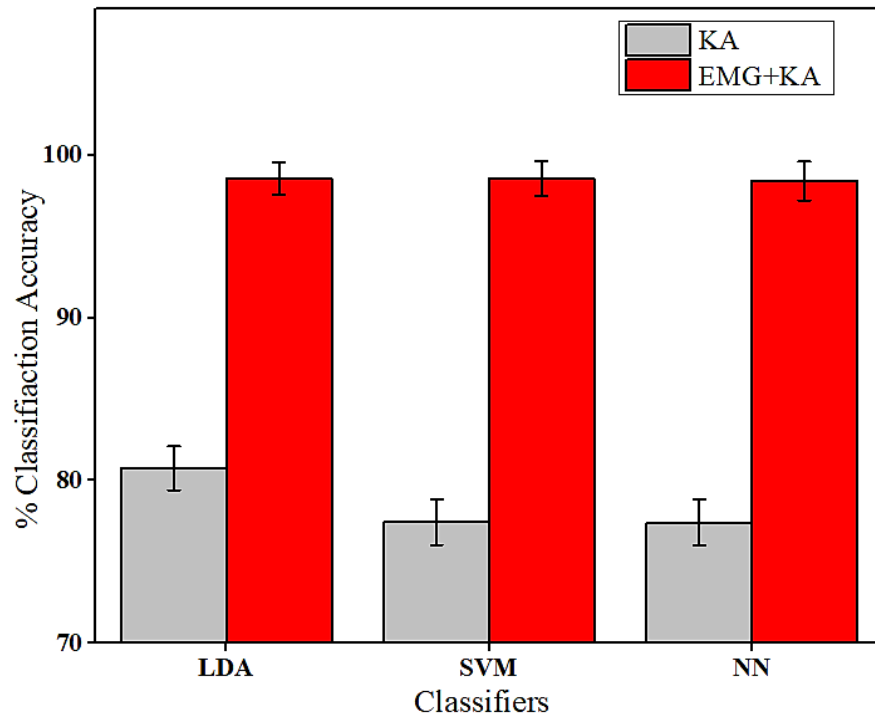


Figure 4.11 Average performance of various classifiers for level-1 classification

4.2.4.2 Feature Selection

Features are considered as information of signal and combination of features, feature vector, has been utilized for training the classifier. The performance of the prediction model is highly dependent on the quality of information fed to train the module. It is always advisable to trim off the irrelevant information to avoid the curse of dimensionality. To select the feature set, an iterative classifier-dependent weighted accuracy feature selection algorithm has been applied for each muscle and classifier. Figure 4.14, Figure 4.13, and Figure 4.14 show the % classification accuracy of SVM, LDA, and NN classifiers, corresponding to the number of features in the feature vector for all six muscles. A rapid improvement in the classifier's performance has been observed, followed by a plateau as the number of features in the feature vector surpasses ten features, which is valid for all classifiers.

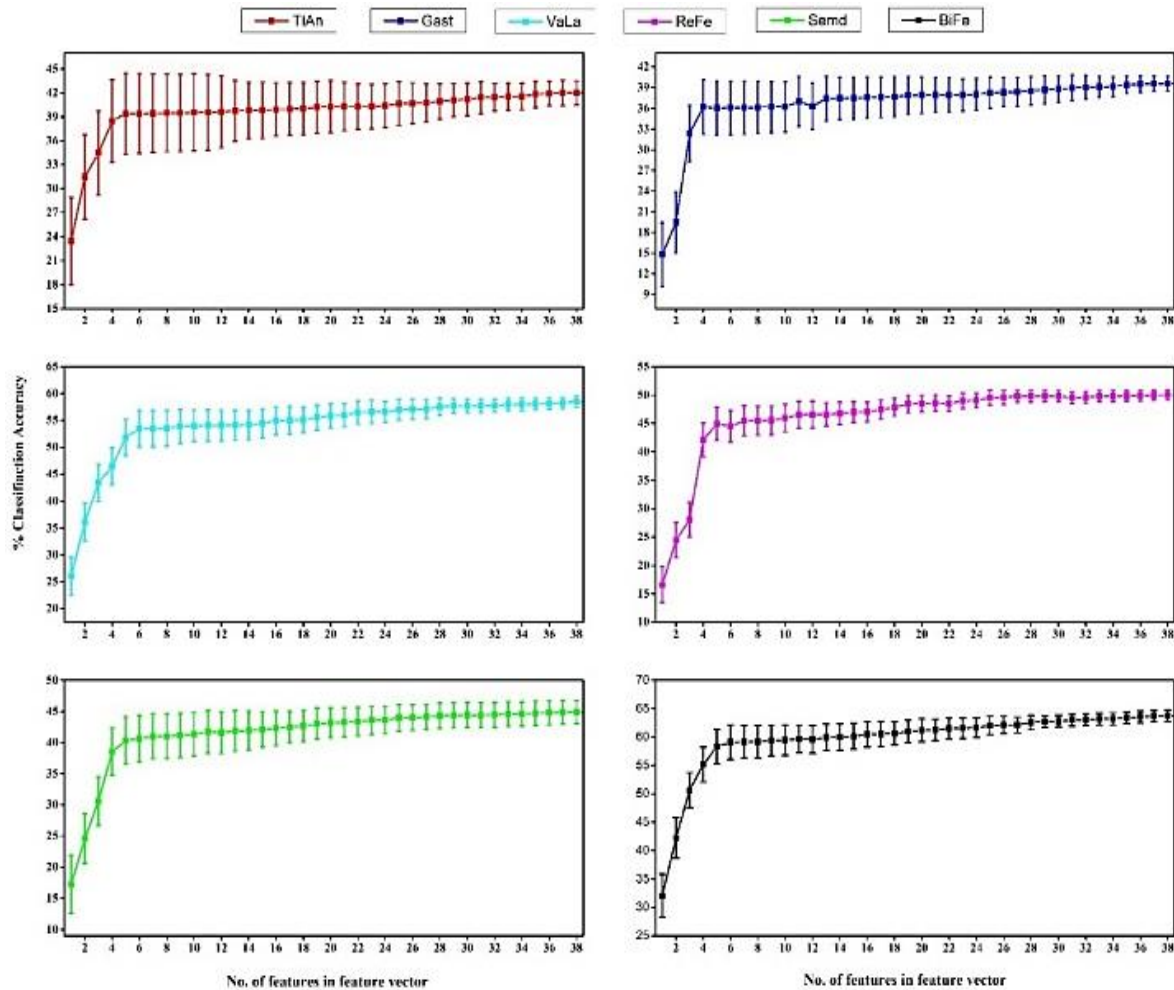


Figure 4.12 % classification accuracy of LDA classifier for different feature vectors

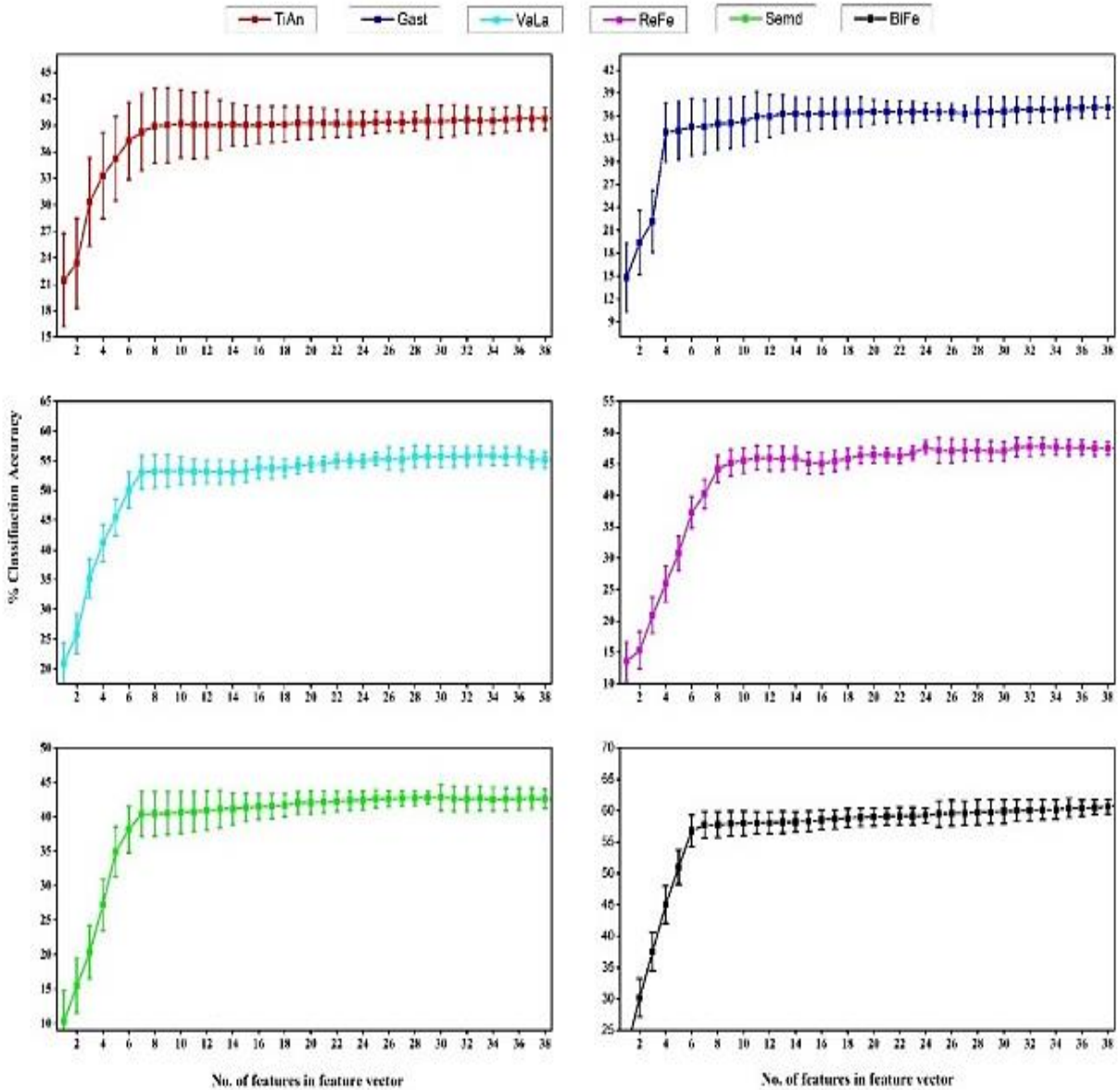


Figure 4.13 % classification accuracy of SVM classifier for different feature vectors

Figure 4.15 shows the selected features for each muscle and classifier. Common features for each classifier, out of ten features, for all six muscles has been estimated and opted for further analysis of individual classifier. Selecting common features of all muscles will make it suitable for hardware implementation where it can be implemented using parallel computing. Time-domain features have shown superior selection frequency over frequency-domain and predictive features for locomotion prediction. In the case of the LDA classifier, the feature vector comes out as MAV, WL, ZC, MYOP, and SSC. For SVM, it comes out as MAV, SSI, WL, ZC, and SSC, whereas, for

the NN classifier, IEMG, MAV, WL, ZC, and SSC are selected for feature vector. Figure 4.16 shows the performance of all classifiers and muscles with selected features vector. The performance of the above-knee muscles (VaLa, ReFe, Semd, and BiFe) have been found superior to the below-knee muscles (TiAn and Gast). Moreover, among the above-knee muscles, the performance of VaLa, and BiFe have been found better than the ReFE and Semd muscles.

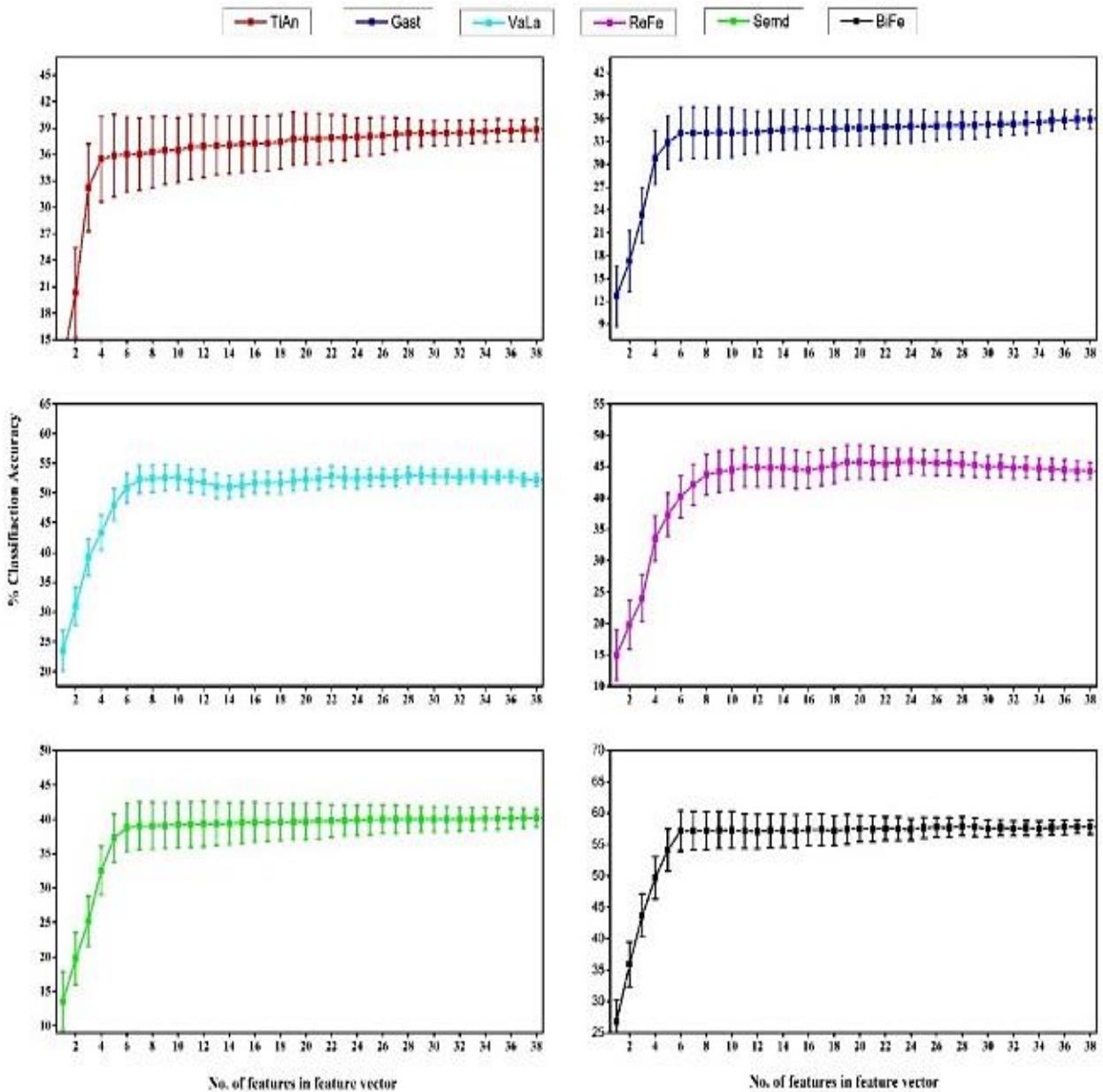


Figure 4.14 % classification accuracy of NN classifier for different feature vectors

LDA	Muscles		Features										
	TiAn	MAV	RMS	WL	ZC	MYOP	WAMP	SSC	MNF	AR1	AR2		
	Gast	IEMG	MAV	SSI	LoG	WL	DASDV	ZC	MYOP	SSC	AR1		
	VaLa	MAV	MAV1	RMS	LoG	WL	ZC	MYOP	WAMP	SSC	H1		
	ReFe	IEMG	MAV	MAV2	VAR	RMS	WL	DASDV	ZC	MYOP	SSC		
	Semd	MAV	MAV1	VAR	WL	AAC	ZC	MYOP	SSC	AR1	AR2		
	BiFe	MAV	SSI	RMS	WL	AAC	ZC	MYOP	SSC	MNF	AR1		
													

Figure 4.15 Selected features of EMG signal with respective classifiers

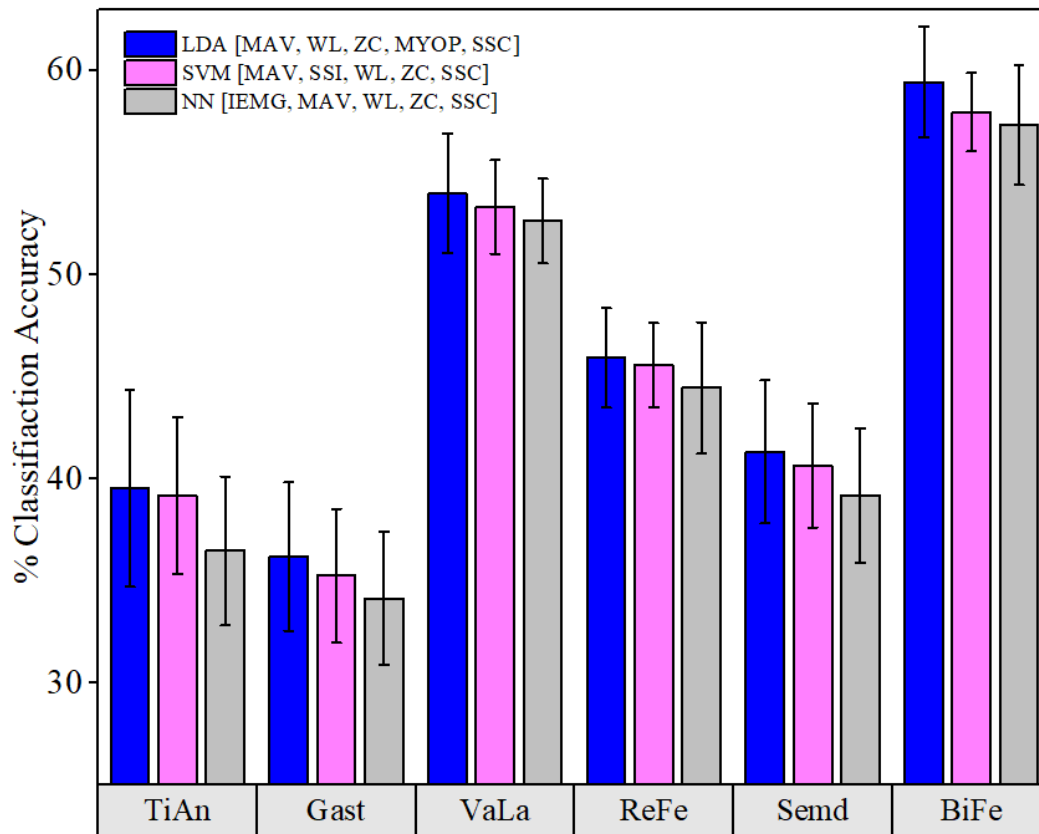


Figure 4.16 Performance of classifiers for each muscle with the selected feature vector

4.2.4.3 Subwindow Size and Muscle Group Selection

The locomotion prediction module, in level-2 classification, utilizes a gait phase-dependent classification approach, as shown in Figure 4.8. A total of four subwindows (WAH, WBT, WAT, and WBH) has been considered over the complete gait cycle. Six subwindow sizes have been considered for comparison (Table 4.4). Further, to select the appropriate muscle group, twenty-seven muscle groups have been formed containing two, three, four, five, and six muscles (Table 4.5). The performance of all three classifiers (LDA, SVM, and NN) have been evaluated for all combinations of subwindow sizes and muscle groups. The classifiers have been trained and tested with feature vector consist of selected features of the EMG signal (Figure 4.15) and KA signal features.

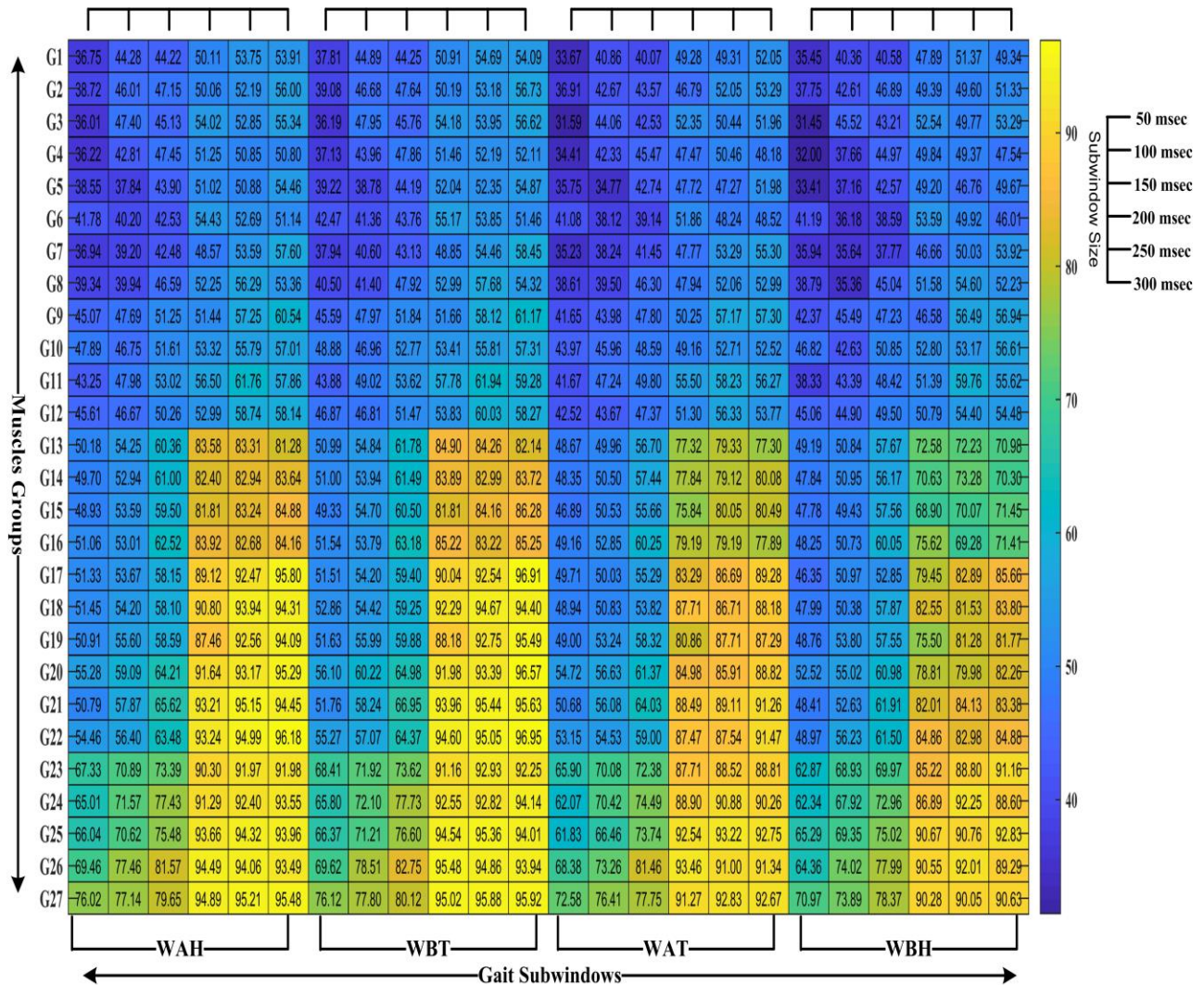


Figure 4.17 Performance of LDA classifier for various combinations of muscle groups and subwindow sizes

Figure 4.17, Figure 4.18, and Figure 4.19 show the performance (% classification accuracy) of LDA, SVM, and NN classifiers, respectively, for different combinations of subwindow sizes and muscle groups. All three classifiers have depicted similar characteristics for different subwindow sizes and muscle group combinations. The results show a significant improvement (One-way ANOVA, p -value<0.05) in performance between lower subwindow sizes (50, 100, and 150 msec) and higher subwindow sizes (200, 250 and 300 msec). Also, there has been observed no significant difference (One-way ANOVA, p -value>0.05) in performance among larger subwindow sizes. So, any subwindow size of ≥ 200 msec can be selected for locomotion prediction. A very large subwindow size incorporates an inherent time delay in the prediction module [151]. Hence, the lowest subwindow size (200 msec) among the larger subwindow sizes (200, 250, and 300 msec) has been selected for further analysis.

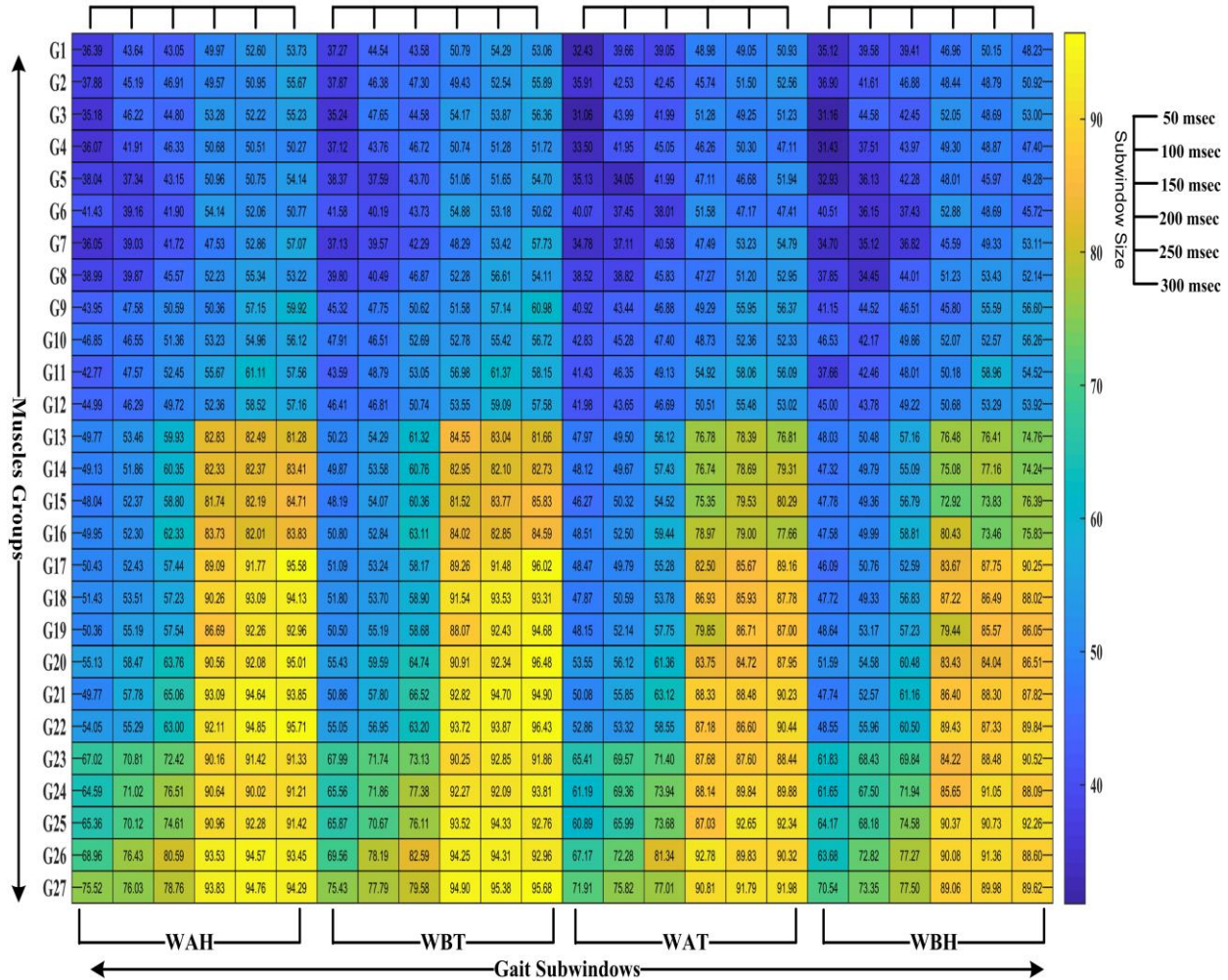


Figure 4.18 Performance of SVM classifier for various combinations of muscle groups and subwindow sizes

Muscle groups with four or more than four muscles (G17-G27) have shown improved performance as compared to muscle groups with two or three muscles (G1-G16). However, the performance of the classifier for muscle groups with four (G17-G22), five (G23-G26), and six (G27) muscles have been found comparable to each other (One-way ANOVA, p -value >0.05). So, any muscle group having four muscles can be selected for locomotion prediction. Here, there are six groups (G17-G22) with a combination of four muscles, *i.e.*, G17 (TiAn, Gast, ReFe, Semd), G18 (TiAn, Gast, VaLa, ReFe), G19 (TiAn, Gast, VaLa, Semd), G20 (TiAn, Gast, ReFe, BiFe), G21 (TiAn, Gast, Semd, BiFe), and G22 (TiAn, Gast, VaLa, BiFe). The performance of individual below-knee muscles (VaLa, ReFe, Semd, BiFe), as shown in Figure 4.16, illustrates that VaLa and BiFe are the top two performing muscles. Hence, for further analysis, muscle group consisting of VaLa and BiFe muscles, *i.e.*, G22 with TiAn, Gast, VaLa, and BiFe muscles, has been opted.

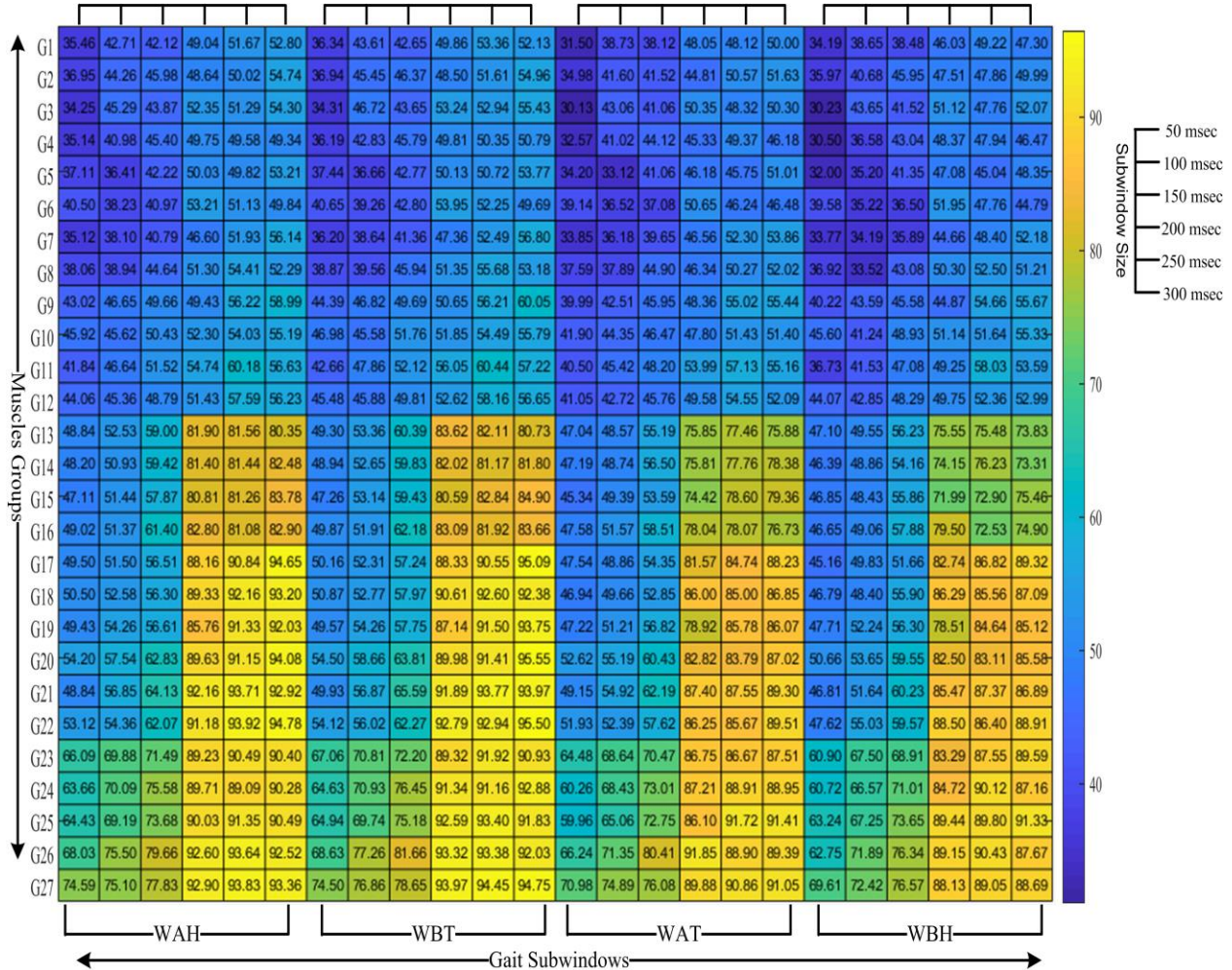


Figure 4.19 Performance of NN classifier for various combinations of muscle groups and subwindow sizes

4.2.4.4 Locomotion Mode Prediction Performance in Steady State

Table 4.7 compiles the information about selected designing parameters based on the results presented in sections 4.2.4.2 and 4.2.4.3. Five time-domain features of the EMG signal along with four features of the KA signal have been used to constitute feature vector. Four muscles (TiAn, Gast, VaLa, and BiFe) and gait subwindow of the size of 200 msec have opted for locomotion prediction. For each subwindow, the dimension of the feature vector comes out as 24, which includes 20 features (4 muscles $\times$ 5 features/muscles) of EMG signal and four features of the KA signal. Further, with the selected parameters, the performance of the locomotion prediction module (level-2 classification) has been estimated for three classifiers (LDA, SVM, and NN).

Table 4.7 Selected designing parameters for level-2 classification

Designing parameters	Opted values
The feature set for EMG signal	[MAV, WL, ZC, MYOP, SSC] for LDA classifier [MAV, SSI, WL, ZC, SSC] for SVM classifier [IEMG, MAV, WL, ZC, SSC] for NN classifier
The feature set for KA	[maximum, minimum, average, variance]
Subwindow size	200 msec
Muscle group	TiAn, Gast, VaLa, and BiFe

Figure 4.20 shows the average % classification accuracy (for ten subjects) of classifiers for different gait subwindows. The hybrid (EMG+KA) information results in better performance of classifiers as compared to only EMG and only KA signals. EMG signal shows the average improvement in classification accuracy of 67.60%, 70.26%, and 68.67% for LDA, SVM, and NN classifiers, respectively, as compared to the KA signal. Whereas by using hybrid information, an improvement of 7.37% has been observed in classification accuracy as compared to EMG signal (One-way ANOVA, p -value<0.05). Similarly, for SVM and NN classifiers, the performance of classifiers has been improved by 5.05% and 4.23% (One-way ANOVA, p -value<0.05). The KA signal carries lesser variation and considered to be a stable signal as compared to the EMG signal [88]. This property of KA signal reflects in classifiers performance, *i.e.*, the classification accuracy achieved by KA signal alone carries lesser variance as compared to EMG signal alone. Moreover, the hybrid (EMG+KA) information carries the advantages of both the signal, which results in a more accurate and stable performance of classifiers.

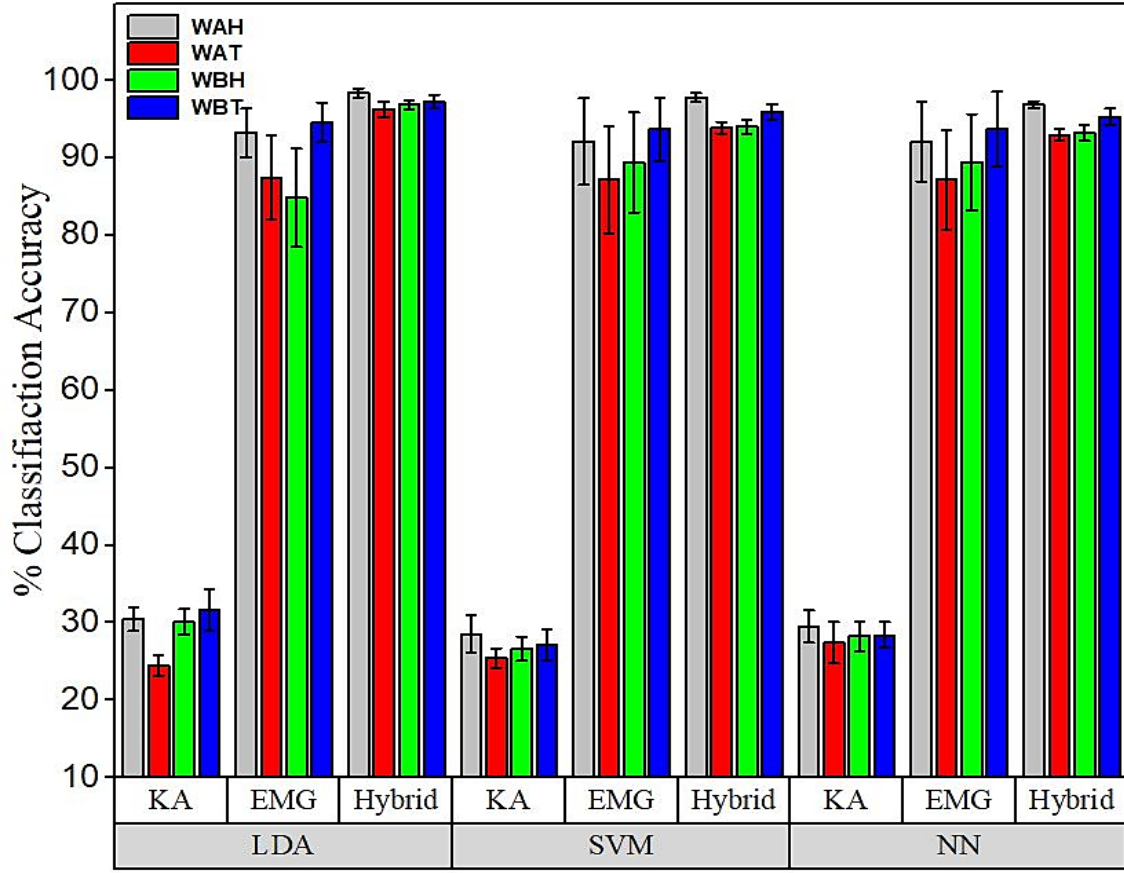


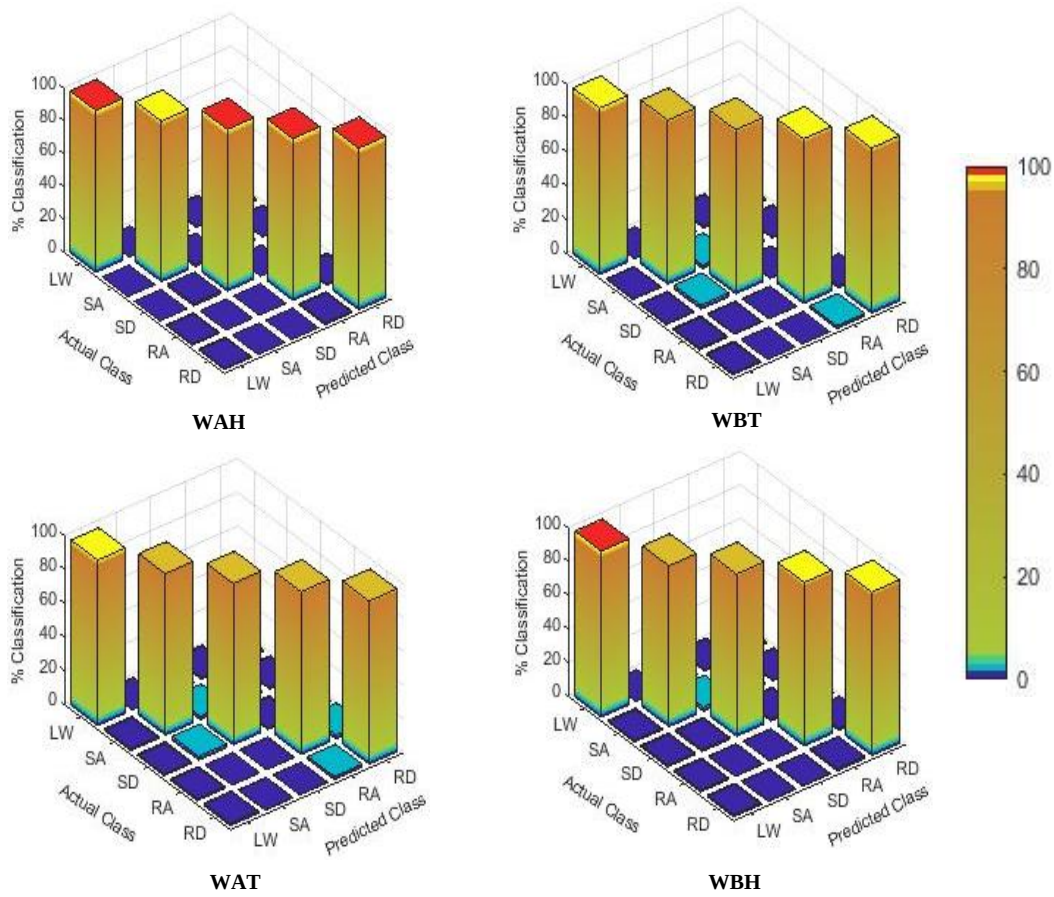
Figure 4.20 Performance of classifiers for locomotion prediction with different input signals

Table 4.8 shows the performance of LDA, SVM, and NN classifiers for each subject while using hybrid information as an input of classifiers. In the case of WAH gait subwindow, LDA, SVM, and NN classifiers display the average % classification accuracy of $98.42 \pm 2.18\%$, $98.42 \pm 2.18\%$, and $98.42 \pm 2.18\%$, respectively. Whereas, for WBT gait subwindow, the performance of LDA, SVM, and NN classifiers have been found as $97.24 \pm 2.24\%$, $95.99 \pm 3.05\%$, and $95.35 \pm 3.16\%$, respectively. Similarly, For WAT and WBH gait subwindows, LDA classifier depicts average % classification accuracy as $96.27 \pm 3.50\%$ and $96.90 \pm 3.40\%$, for SVM classifier it has been found as $93.88 \pm 3.61\%$ and $94.03 \pm 3.62\%$ and for NN classifiers it has been found as $92.98 \pm 3.32\%$ and $93.25 \pm 3.54\%$, respectively. It has been observed from the results that gait subwindows of the stance phase (WAH and WBT) result in better performance of classifiers as compared to gait subwindows of the swing phase (WAT and WBT). The possible reason for such results is due to minimal information in the EMG signal during the swing phase, and the muscle activation pattern shows similar characteristics for different locomotion modes [19].

Table 4.8 % classification accuracy of all classifiers for locomotion prediction (level-2)

NN classifier				
Subject	Subwindows			
	WAH	WBT	WAT	WBH
S1E2	97.76 $\pm$ 1.66	96.45 $\pm$ 1.94	96.38 $\pm$ 2.66	97.38 $\pm$ 2.59
S2E2	98.45 $\pm$ 2.76	97.31 $\pm$ 2.22	97.05 $\pm$ 2.72	97.30 $\pm$ 3.64
S3E2	99.36 $\pm$ 2.18	98.06 $\pm$ 2.35	95.08 $\pm$ 3.90	96.08 $\pm$ 2.97
S4E2	98.37 $\pm$ 1.98	96.99 $\pm$ 2.49	97.56 $\pm$ 4.02	97.23 $\pm$ 3.66
S5E2	99.34 $\pm$ 2.18	98.78 $\pm$ 2.60	96.75 $\pm$ 3.57	96.33 $\pm$ 2.49
S6E2	98.19 $\pm$ 1.95	96.72 $\pm$ 2.23	94.70 $\pm$ 3.49	96.88 $\pm$ 3.82
S7E2	98.29 $\pm$ 1.97	96.96 $\pm$ 1.84	95.50 $\pm$ 3.68	97.83 $\pm$ 3.86
S8E2	97.42 $\pm$ 2.37	98.48 $\pm$ 2.02	97.72 $\pm$ 3.20	96.80 $\pm$ 3.79
S9E2	98.74 $\pm$ 2.35	96.61 $\pm$ 1.94	95.81 $\pm$ 4.54	97.07 $\pm$ 3.44
S10E2	98.27 $\pm$ 2.29	96.01 $\pm$ 2.80	96.15 $\pm$ 3.22	96.11 $\pm$ 3.73
SVM classifier				
Subject	Subwindows			
	WAH	WBT	WAT	WBH
S1E2	97.10 $\pm$ 3.22	94.35 $\pm$ 3.53	93.50 $\pm$ 4.19	95.19 $\pm$ 3.70
S2E2	98.41 $\pm$ 2.71	96.67 $\pm$ 2.89	94.97 $\pm$ 3.32	95.17 $\pm$ 3.73
S3E2	98.50 $\pm$ 2.73	96.02 $\pm$ 2.99	94.62 $\pm$ 3.28	92.75 $\pm$ 3.40
S4E2	97.43 $\pm$ 2.80	96.38 $\pm$ 3.01	94.19 $\pm$ 3.36	93.28 $\pm$ 3.24
S5E2	98.66 $\pm$ 2.26	96.46 $\pm$ 2.30	92.46 $\pm$ 2.65	94.99 $\pm$ 3.44
S6E2	97.43 $\pm$ 3.36	95.85 $\pm$ 3.48	93.99 $\pm$ 4.01	94.56 $\pm$ 4.45
S7E2	97.54 $\pm$ 3.08	96.47 $\pm$ 3.14	94.61 $\pm$ 3.72	94.41 $\pm$ 3.77
S8E2	97.02 $\pm$ 2.81	97.85 $\pm$ 2.90	93.84 $\pm$ 3.83	93.63 $\pm$ 3.59
S9E2	98.08 $\pm$ 3.34	95.07 $\pm$ 3.46	92.86 $\pm$ 4.34	94.04 $\pm$ 4.08
S10E2	98.10 $\pm$ 2.57	94.83 $\pm$ 2.78	93.73 $\pm$ 3.38	92.27 $\pm$ 2.83
NN classifier				
Subject	Subwindows			
	WAH	WBT	WAT	WBH
S1E2	96.01 $\pm$ 2.89	94.09 $\pm$ 3.25	92.97 $\pm$ 3.60	93.08 $\pm$ 4.38
S2E2	97.37 $\pm$ 2.40	96.29 $\pm$ 3.16	93.72 $\pm$ 3.30	95.09 $\pm$ 3.25
S3E2	96.67 $\pm$ 2.89	94.80 $\pm$ 3.21	93.74 $\pm$ 3.02	91.95 $\pm$ 2.96
S4E2	96.76 $\pm$ 2.45	96.01 $\pm$ 3.04	93.37 $\pm$ 3.85	92.11 $\pm$ 3.93
S5E2	97.10 $\pm$ 3.56	95.07 $\pm$ 2.51	91.08 $\pm$ 2.51	93.59 $\pm$ 3.49
S6E2	96.85 $\pm$ 2.05	95.33 $\pm$ 3.53	93.56 $\pm$ 3.64	94.37 $\pm$ 3.91
S7E2	96.57 $\pm$ 2.32	96.18 $\pm$ 3.05	93.47 $\pm$ 3.29	93.56 $\pm$ 3.22
S8E2	96.73 $\pm$ 2.78	97.47 $\pm$ 3.14	92.71 $\pm$ 3.10	92.93 $\pm$ 3.13
S9E2	97.78 $\pm$ 2.50	94.15 $\pm$ 3.40	92.29 $\pm$ 3.89	94.02 $\pm$ 3.85
S10E2	96.98 $\pm$ 2.17	94.12 $\pm$ 2.96	92.88 $\pm$ 2.96	91.76 $\pm$ 3.32

Figure 4.21 shows the confusion matrix of LDA, SVM, and NN classifiers for locomotion prediction using hybrid signals. It provides the detailed performance of classifiers and highlights the situation of errors. It has been observed from the results that LW is relatively distinguishable from SA and SD locomotion. Most of the errors have been found due to confusion between LW and RA or RD locomotion. The classification performance for LW locomotion has been found consistent for all four gait subwindows. However, for other locomotion modes (SA, SD, RA, and RD), the classification performance decreases during the swing phase gait subwindows. The overall average performance of LDA, SVM, and NN classifiers for all gait subwindows have been found as $97.21 \pm 0.78\%$, $95.43 \pm 1.61\%$, and $94.61 \pm 1.59\%$, respectively. The performance of classifiers have been found significantly different (One-way ANOVA, $p\text{-value} < 0.05$).



(a) LDA

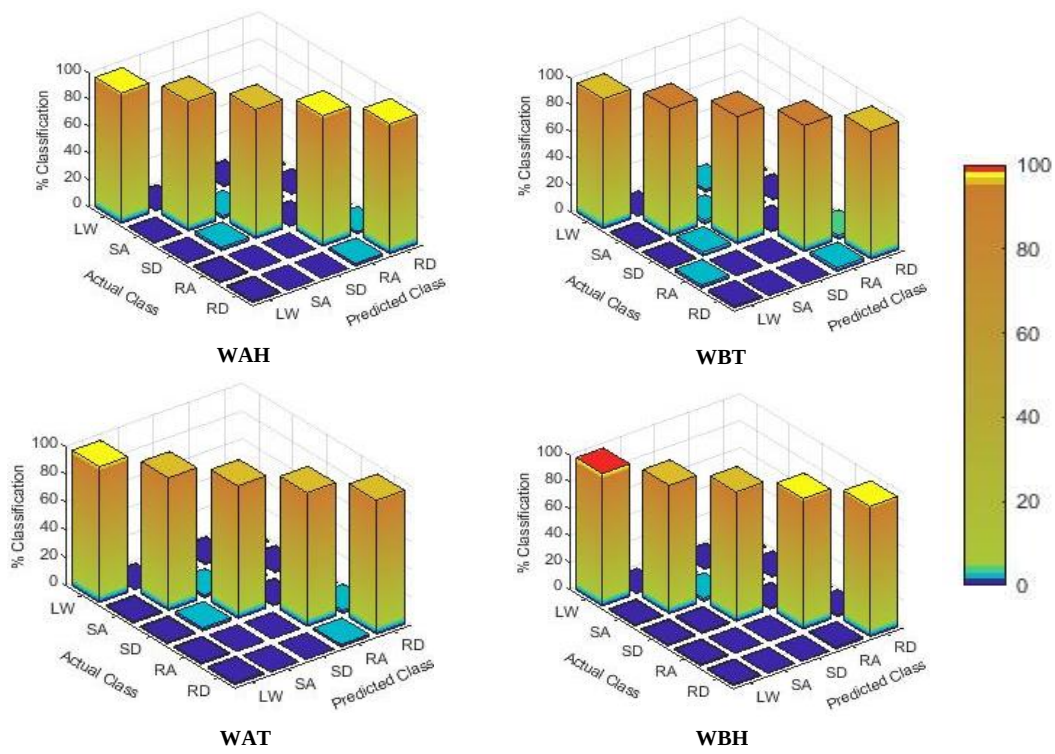
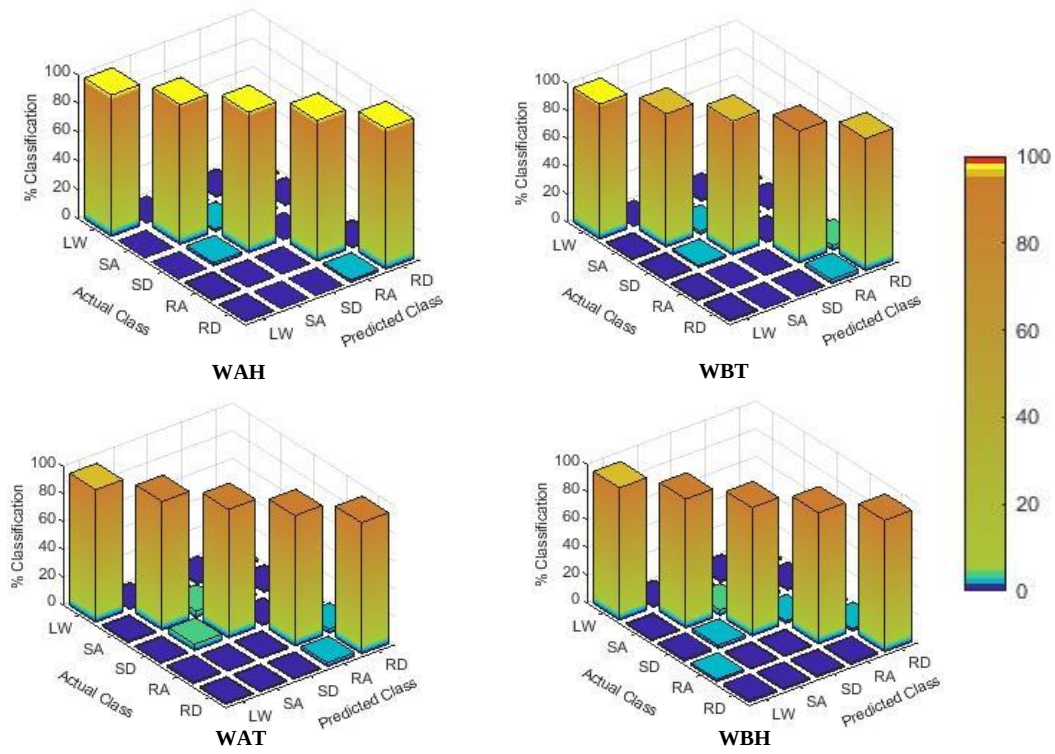


Figure 4.21 Confusion matrix illustration of all classifiers for locomotion prediction

4.2.4.1 Locomotion Mode Prediction Performance for Transitions

The performance of the locomotion prediction module (level-2 classification) has been estimated for locomotion transitions. Nine locomotion transitions (Figure 3.5) have been considered for the presented research work. Table 4.9 summarizes the performance of LDA, SVM, and NN classifiers for locomotion transitions.

The results show the highest transition errors during $LW \leftrightarrow RA/RD$, whereas, for $LW \leftrightarrow SA/SD$ and $LW \rightarrow STD$, lower transition errors have been observed. These results are well supported by the basic of human biomechanics pattern. The lower limb joint angles and the gait cycle shows very similar variations during level and ramp walk. A minor difference in joint angles has been observed due to the ramp inclination. However, this variation gets prominent as the ramp inclination increases. Also, for both the terrain, the human body moves forward through the push-off provided at the toe-off event of the gait cycle. Due to the aforementioned reasons, the classifiers show higher transition errors for $LW \leftrightarrow RA/RD$ transitions. The average % of missed $LW \leftrightarrow RA/RD$ transitions have been found as 7.25%, 10.25%, and 10.75% for LDA, SVM and NN classifiers, respectively.

In the case of level and stair walk, the lower limb joint angles and gait cycle changes significantly. During the level walk gait cycle, the knee angle varied in a manner so that the human body able to move forward. Whereas, during the stair walk, the knee angle varied in a way so that the human body able to move upward/downward in order to move up/down on stairs. Similar variations in the ankle-foot joint angle can also be observed [36]. In the same manner, the EMG signal of muscles also varied to attain the variation in lower limb joint angles. These significant differences in lower limb biomechanics and EMG signal pattern during level and stair walk have easily identified by the classifiers. Hence, these transitions have been recognized with high accuracy by the classifiers. Average % of missed $LW \leftrightarrow SA/SD$ transitions have been found as 2.5%, 6.75%, and 6.00% for LDA, SVM and NN classifiers, respectively. The overall average % of missed locomotion transitions have been found as 4.56%, 7.78%, and 8.11% for LDA, SVM and NN classifiers, respectively (One-way ANOVA, $p\text{-value} < 0.05$).

Table 4.9 Subject wise missed locomotion transitions details for all classifiers

Subject	LDA classifier									%Err _{Tr}
	LW-RD	RD-LW	LW-SA	SA-LW	LW-SD	SD-LW	LW-RA	RA-LW	LW-STD	
S1E2	1	1	0	0	0	0	1	0	0	3.33
S2E2	1	1	0	0	0	0	1	1	0	4.44
S3E2	1	1	0	0	0	1	0	0	0	3.33
S4E2	0	1	0	1	1	0	1	2	0	6.67
S5E2	1	1	0	0	0	0	1	0	1	4.44
S6E2	0	1	0	0	0	1	1	1	0	4.44
S7E2	1	1	0	0	0	1	0	1	0	4.44
S8E2	0	1	1	1	0	0	0	1	1	5.56
S9E2	1	0	1	0	0	0	1	1	0	4.44
S10E2	1	0	1	0	0	1	0	1	0	4.44
Total	7	8	3	2	1	4	6	8	2	4.56
Subject	SVM classifier									%Err _{Tr}
	LW-RD	RD-LW	LW-SA	SA-LW	LW-SD	SD-LW	LW-RA	RA-LW	LW-STD	
S1E2	2	1	0	0	0	1	0	1	0	5.56
S2E2	1	1	1	1	0	1	1	0	0	6.67
S3E2	0	2	1	0	0	0	1	2	0	6.67
S4E2	1	1	0	1	1	1	2	1	0	8.89
S5E2	0	1	1	1	1	0	1	1	0	6.67
S6E2	1	0	1	1	0	1	2	1	0	7.78
S7E2	1	1	1	0	1	1	1	2	1	10.00
S8E2	1	1	1	1	1	1	1	2	0	10.00
S9E2	1	0	0	0	1	0	1	1	1	5.56
S10E2	1	1	2	1	1	1	1	1	0	10.00
Total	9	9	8	6	6	7	11	12	2	7.78
Subject	NN Classifier									%Err _{Tr}
	LW-RD	RD-LW	LW-SA	SA-LW	LW-SD	SD-LW	LW-RA	RA-LW	LW-STD	
S1E2	1	2	0	1	1	0	1	0	1	7.78
S2E2	0	1	1	1	0	1	0	1	0	5.56
S3E2	1	1	1	0	1	0	2	1	1	8.89
S4E2	1	1	0	0	0	1	2	0	1	6.67
S5E2	1	0	1	0	1	1	1	0	1	6.67
S6E2	2	1	0	1	0	0	1	1	1	7.78
S7E2	1	2	0	0	1	1	1	1	0	7.78
S8E2	1	1	1	1	0	1	1	2	0	8.89
S9E2	1	2	1	1	1	1	2	1	1	12.22
S10E2	1	2	1	0	1	1	1	1	0	8.89
Total	10	13	6	5	6	7	12	8	6	8.11

The selection of suitable muscles for ankle-foot movements is necessary to achieve effective control of prosthesis. EMG signal of six lower limb below-knee muscles have been compared on the basis of their activation level, activation duration and fatigue for repetitive DF/PF and DFW/PFW movements of ankle-foot. TiAn and Gast muscles are found appropriate for ankle-foot movements. Further, a two-level classification approach has been implemented for activity and locomotion identification. The performance of three classifiers (LDA, SVM and NN) have been compared for two activities and five daily life locomotion. Level-1 classification shows average % classification accuracy of $98.56 \pm 0.99\%$ for LDA classifier with EMG signal of four muscles (TiAn, Gast, VaLa and BiFe) and KA signal. At level-2 classification a gait-phase dependent classification approach has been implemented. Four gait subwindows (WAH, WBT, WAT and WBH) of size 200 msec. along with group of four muscles (TiAn, Gast, VaLa and BiFe) have been selected for locomotion prediction. LDA classifier with EMG signal and KA signal information has shown the best average % classification accuracy $97.21 \pm 0.78\%$ for steady state locomotion prediction and average % transition error 4.56% for locomotion transitions. The results have shown the superiority of LDA classifier over other compared classifiers. Hence, it has been preferred for activity and locomotion prediction.

Chapter 5

Ankle Joint Angle Estimation & Prototype Development

This chapter has two sections; the first section describes the designing of the ankle joint angle estimation module, and the second section presents the details of the prosthesis prototype and its control. Section 5.1 describes the methodology, signal processing, and performance measures utilized for the human ankle joint angle estimation along with results. In the subsequent part of the chapter, section 5.2, details of developed prosthesis prototype and its control sequence have been presented.

5.1 Ankle Joint Angle Estimation

The interaction between humans and robots had a vast history. It is still a continuously growing and clinically relevant area of research. With the technological advancement, the requirement of natural operation and adaptive interface for prostheses operation is increasing exponentially. The seamless operation of the prosthesis is achieved by incorporating movement anticipation property and continuously estimating the angular position of the limb joint. It ultimately provides more natural control over the prostheses and improves its efficacy. The following section describes the ankle joint angle estimation module design for prosthesis control.

5.1.1 Methodology

EMG signal is more predictive and precedes the angular orientation of the limb. However, its low signal quality poses challenges to achieve robust control over prostheses. Inertial sensor signals are more stable and reliable than the EMG signal. Moreover, the EMG signal is entirely random and unpredictable in nature, even for the same and repetitive limb movements. On the other hand, the inertial sensor signals are reasonably similar for a particular limb movement. The inertial sensors signal did not capture the effort/force contributed by the human body for a particular limb movement, whereas, this information can be estimated through the EMG signal. In contrast to the inertial sensor signal, the EMG signal is profoundly affected by muscle fatigue. Hence, the fusion of inertial sensor signals with the EMG signal overcomes the drawbacks of each other and improves the performance of the prediction model. NN-based algorithms are considered as a

suitable prediction model for the lower limb joint angle. The modulation in the human lower limb joint angle is cyclic in nature during walking, so incorporating time history information will be very effective and improve the performance of the estimation model [58,100,124,152]. The present research work used time history information of EMG signal with KA signal as inputs to the NN-based prediction model for continuous estimation of ankle joint angle. EMG signal of two lower limb below-knee muscles found suitable for ankle joint movements in section 4.1 (TiAn and Gast) have been opted along with KA signal.

The separate joint angle estimation model has been designed for each locomotion (LW, SA, SD, RA, and RD). Data set acquired during experiment-2, presented in section 3.2.2, has been utilized for training and testing the proposed model. The implemented approach to continuously predict joint angle using natural muscle activity (EMG) provides opportunities for direct (transparent) control of a prosthesis joint by the user. The model's angle estimation capability could prove particularly useful for providing a more biomimetic ankle response during different locomotion.

5.1.2 Signal Processing and Learning Algorithm

5.1.2.1 Signal Processing

Figure 5.1 shows the block diagram consisting of steps utilized for ankle joint angle estimation. EMG signal is inherently a low power and stochastic signal. Various noises easily contaminate it during signal acquisition. It is necessary to preprocess the EMG signal before utilizing it for further analysis. The raw EMG signal has been filtered at the first place using zero lag, 4th order, bandpass Butterworth filter with the frequency band of 10-450 Hz followed by 50 Hz notch filter [134]. After that, the filtered EMG signal of individual muscle has been normalized using max normalization to trim out the speed variation during different trials [153]. The EMG signal is inherently random in nature, and it swings around zero mean. Hence, to capture information on both side signals, full-wave rectification of signal has been performed using Eq. (5.1).

$$EMG_{rect}(t) = \begin{cases} EMG(t) & \text{if } EMG(t) > 0 \\ -1 * EMG(t) & \text{if } EMG(t) \leq 0 \end{cases} \quad (5.1)$$

where, $EMG(t)$ is normalized EMG signal and, $EMG_{rect}(t)$ is a full-wave rectified EMG signal.

The amplitude of EMG signal is directly correlated with the contraction level of the muscle, and an indicator of change in joint angle that carries low-frequency characteristics [121,124,154]. The

rectified EMG signal has been processed through zero lag 2nd order low-pass Butterworth filter with cutoff frequency of 10 Hz to retain only low-frequency information of EMG signal. The EMG signal is of very low amplitude (mV) and recorded non-invasively from the human body. So, it has a higher probability of getting contaminated due to environmental noise and electrode movements while recording. Whereas the joint angles are estimated using IMU sensor signals, which provides a very high amplitude (V) as compared to the EMG signal. Hence, lower limb joint angle signals are more robust, strong, and less prone to noise as compared to EMG signals [143]. It has been passed through zero lag 2nd order low-pass Butterworth filter of 10 Hz cut off frequency to remove the high-frequency noise generated due to sensors movements and involuntary limb movement [155]. The enveloped EMG signal and lower limb joint angle signals have been sub-sampled at 100 Hz for further analysis [143]. Finally, complete data of each subject has been segregated into two parts, namely, training and testing data. Training data and testing data have been utilized for training and testing the learning algorithm.

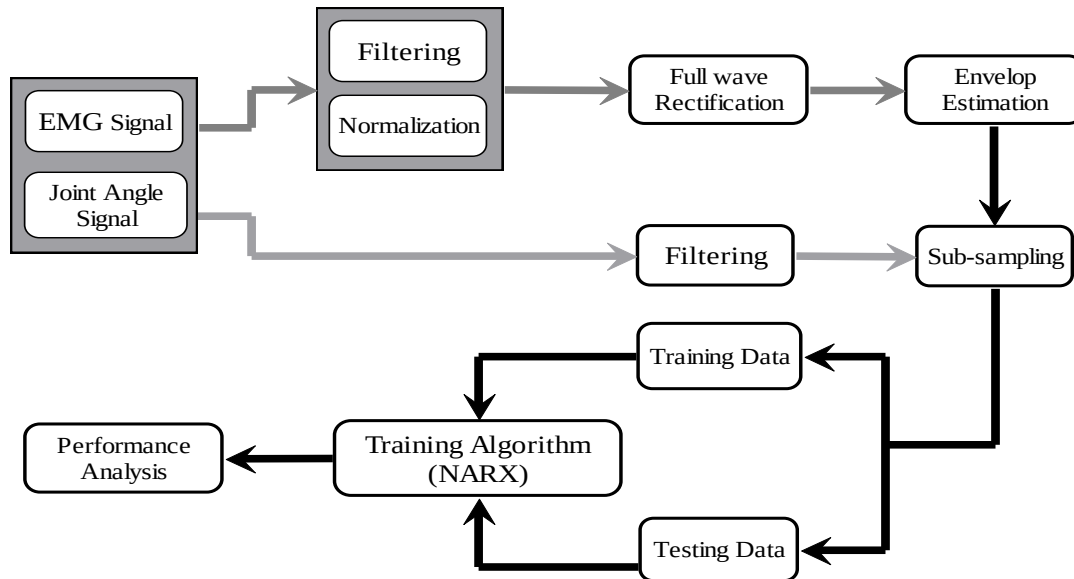


Figure 5.1 Signal processing steps for ankle joint angle estimation

5.1.2.2 Learning Algorithm

NNs had already proven its efficacy for an extensive range of problems such as; pattern classification, optimization, prediction, and clustering, *etc.* It is a black-box modeling technique having the potential to translate a non-linear mapping between multi-dimensional input and output space, even if the relations between those inputs and outputs are unknown. NNs are developed as a mathematical model, which depends on the prior knowledge of the system to be modeled. In

view of that, the present research problem (ankle joint angle prediction) is a time-series prediction problem with cyclic nature.

Non-negative Autoregressive Exogenous (NARX) neural network has been considered as a good predictor for time series problems. It had been used to model various nonlinear dynamic systems, including time series modeling. It is considered as a DRNN with feedback connections that enclose several layers of the network. It also provides the ability to incorporate past values of predicted or/and actual time series or/and predictors. This property of NARX neural network makes it more suitable for the present research problem in which time history information of inputs (EMG and KA) and output (ankle joint angle) carries a significant amount of information. The general mathematical relationship between inputs and outputs for a NARX neural network model is represented as Eq. (5.3) [156]. It is used to continuously map EMG signal and KA into ankle joint angle.

$$y(t) = f(x(t-1), x(t-2), \dots, x(t-t_d), y(t-1), y(t-2), \dots, y(t-t_d)) \quad (5.2)$$

where, $y(t)$ is estimated output at time t ; $x(t)$ is N -dimensional input vector of two-channel EMG signal and KA, t_d is delay order in input and feedback output, and f is functional relation relating inputs and output.

Figure 5.2 shows the basic block diagram of the NARX model, which consists of the input layer, one hidden layer with nonlinear units, and an output layer with linear units. The input ($x(t)$) containing EMG activity of two muscles and KA signal, has been passed through tapped delay lines along with previously estimated ankle joint angle to a hidden layer having nonlinear units (f_h). The output of hidden layer ($y_h(t)$) has been further processed through linear units (f_o) to estimate the ankle joint angle ($y(t)$) over time. The input layer of the model contains enveloped EMG signal recorded from two below-knee muscles, KA and estimated ankle joint angle as feedback, whereas the output layer has a single output corresponding to the estimated ankle joint angle. All the inputs of the model have been passed to the model with added delay along with estimated output as feedback [124].

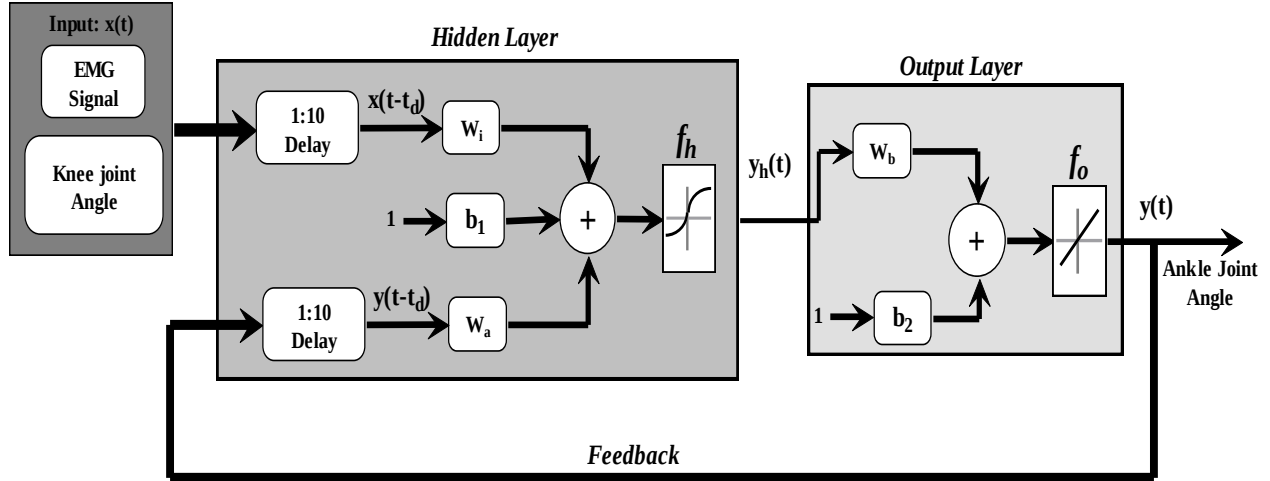


Figure 5.2 Basic block diagram of the NARX model applied for ankle joint angle prediction

The proposed NARX model has been trained using supervised learning (backpropagation) algorithm to minimize the MSE between the predicted and actual ankle joint angles. Figure 5.2 and Eq. (5.2) suggest that the performance of the model is dependent on the number of neurons in the input layer, *i.e.*, the order of the delay and neurons in the hidden layer. The number of neurons in the input layer is calculated as the multiplication of the number of input channels (N), the number of output feedback (l), and the order of delay (m). So far, the number of input channels and output feedback is fixed, *i.e.*, 3 (two-channel EMG signal and KA) and 1 (ankle joint angle), respectively. However, the order of delay and number of neurons in the hidden layer is still needed to be selected further.

5.1.3 Performance Measures

The performance of the proposed method has been evaluated for each locomotion and subject. LOOCV scheme has been utilized for performance assessment of the training model. Two performance measures, RMSE and CCoef, have been used to assess the performance of the angle estimation model. RMSE has been quantified using Eq. (5.3), it is the error between the estimated and actual joint angle so, and its smaller value signifies the higher angle estimation accuracy. CCoef has been estimated using Eq. (5.4), it implies the degree of fit between actual and estimated joint angles [157]. It ranges between 0 to 1, higher the value better the consistency.

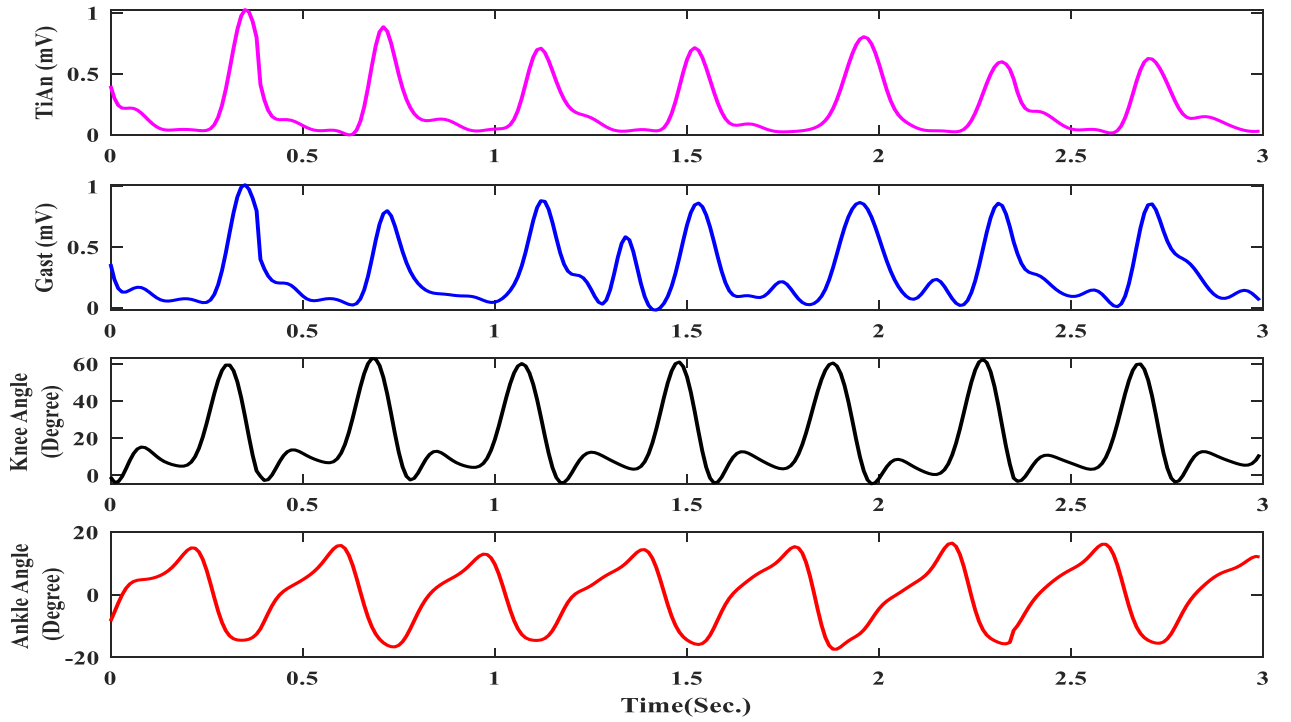
$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (\theta_{act}(i) - \theta_{est}(i))^2}{n}} \quad (5.3)$$

$$CCoef = \frac{\sum_{i=1}^n (\theta_{act}(i) - \overline{\theta_{act}})(\theta_{est}(i) - \overline{\theta_{est}})}{\sqrt{\sum_{i=1}^n (\theta_{act}(i) - \overline{\theta_{act}})^2 \sum_{i=1}^n (\theta_{est}(i) - \overline{\theta_{est}})^2}} \quad (5.4)$$

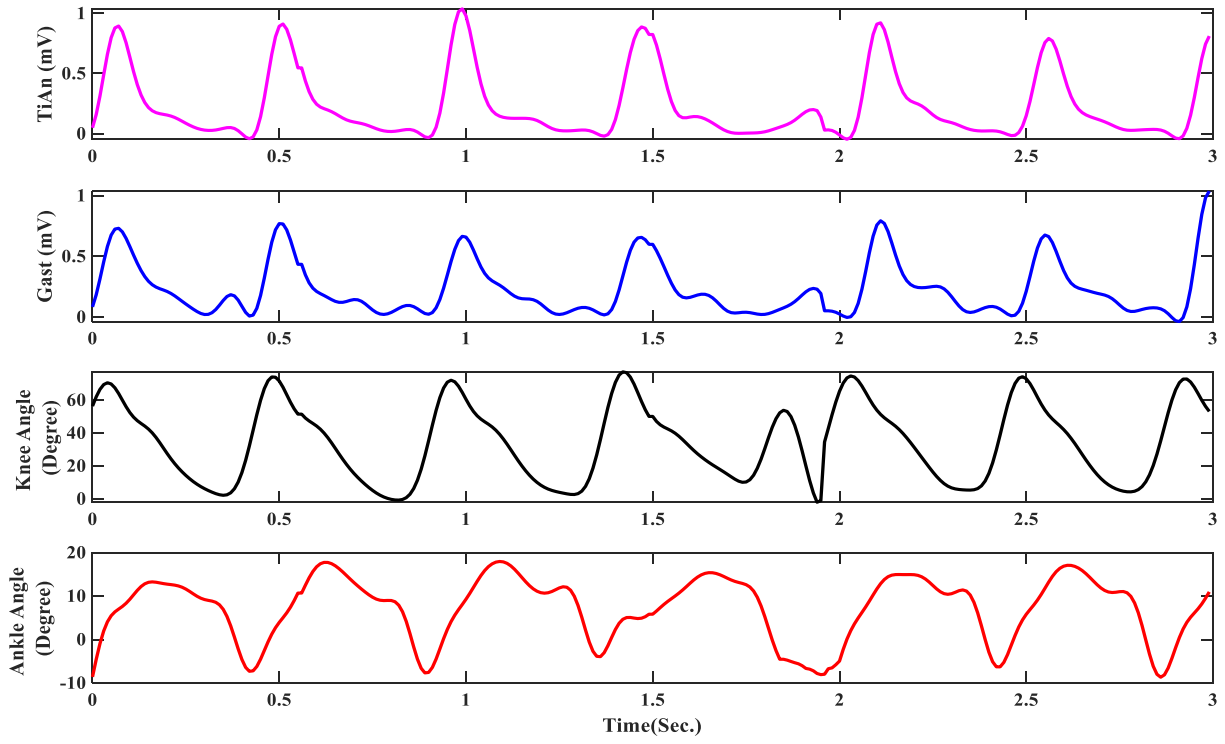
where, θ_{act} and θ_{est} are actual and predicted ankle joint angle respectively, n is the number of sample points in each trial and $\overline{\theta_{act}}$ and $\overline{\theta_{est}}$ are average actual and predicted ankle joint angles respectively over each trial.

5.1.4 Results and Discussion

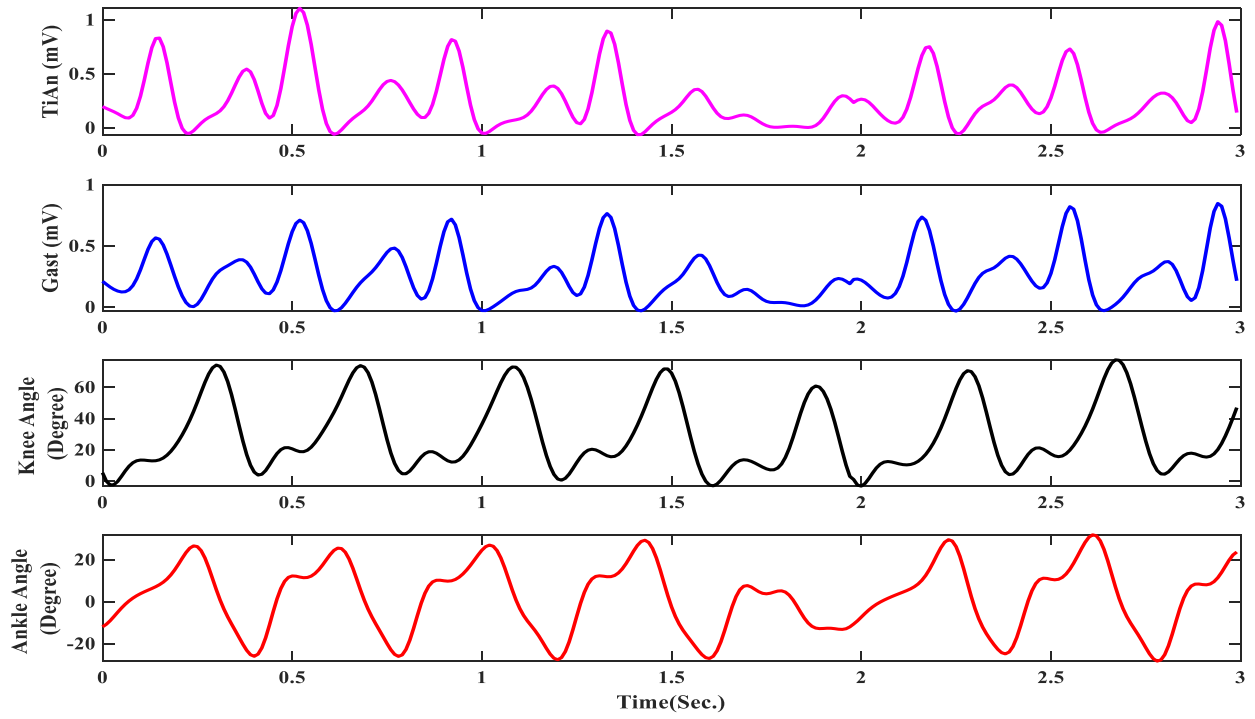
EMG signal of muscles (responsible for ankle movement, *i.e.*, TiAn and Gast) along with KA signal has been used for ankle joint angle estimation. The complexity of NARX has been reduced by selecting suitable inputs. Figure 5.3 shows the EMG envelop of TiAn and Gast muscles along with KA and ankle joint angles for all five locomotion (LW, RA, RD, SA, and SD). A rhythmic variation and coordination in knee and ankle joint angles have been observed for all locomotion [158]. Hence, the proposed method utilizes KA in addition to EMG signals as inputs to the prediction model for ankle joint angle estimation.



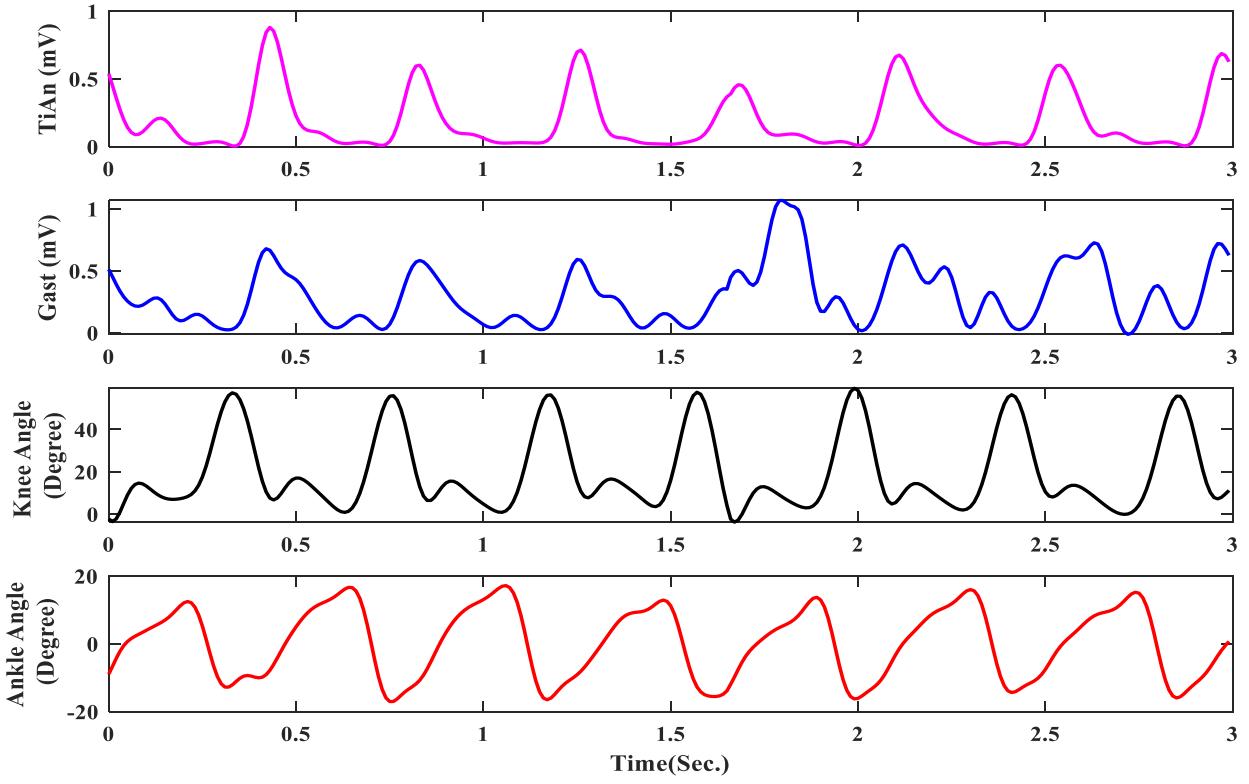
(a) LW



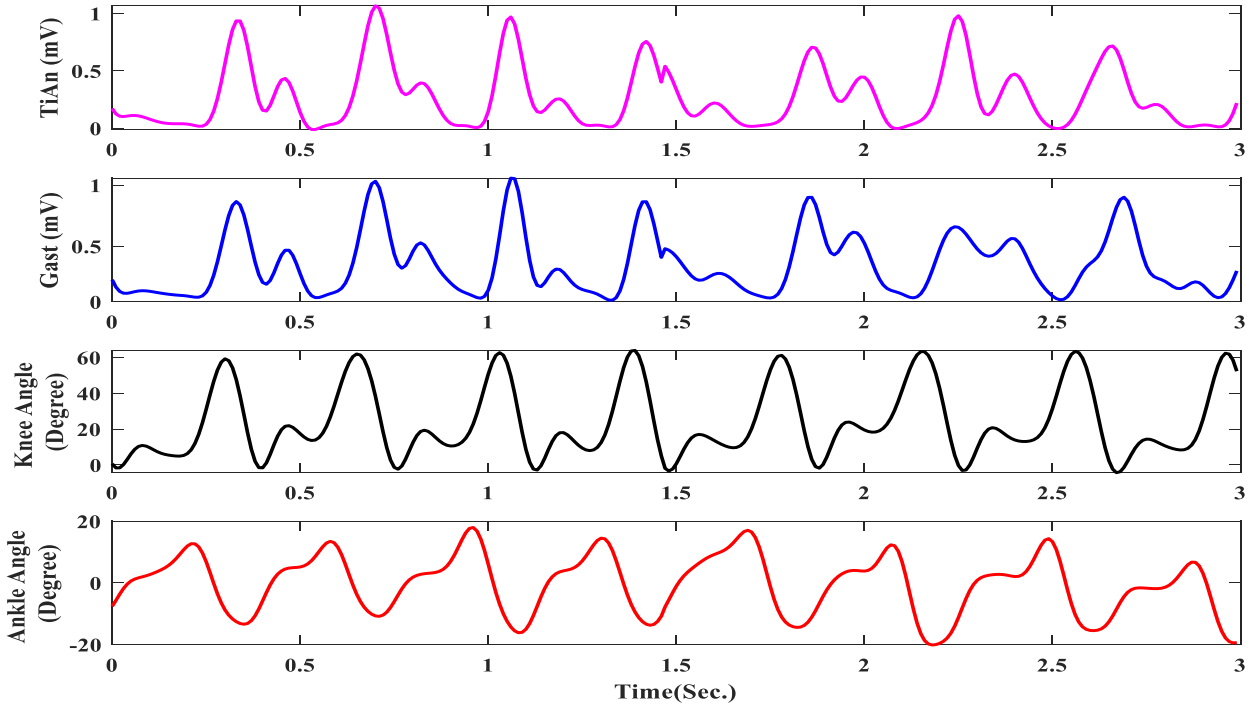
(a) SA



(b) SD



(c) RA



(d) RD

Figure 5.3 Enveloped EMG and lower limb joint angle signal for various locomotion

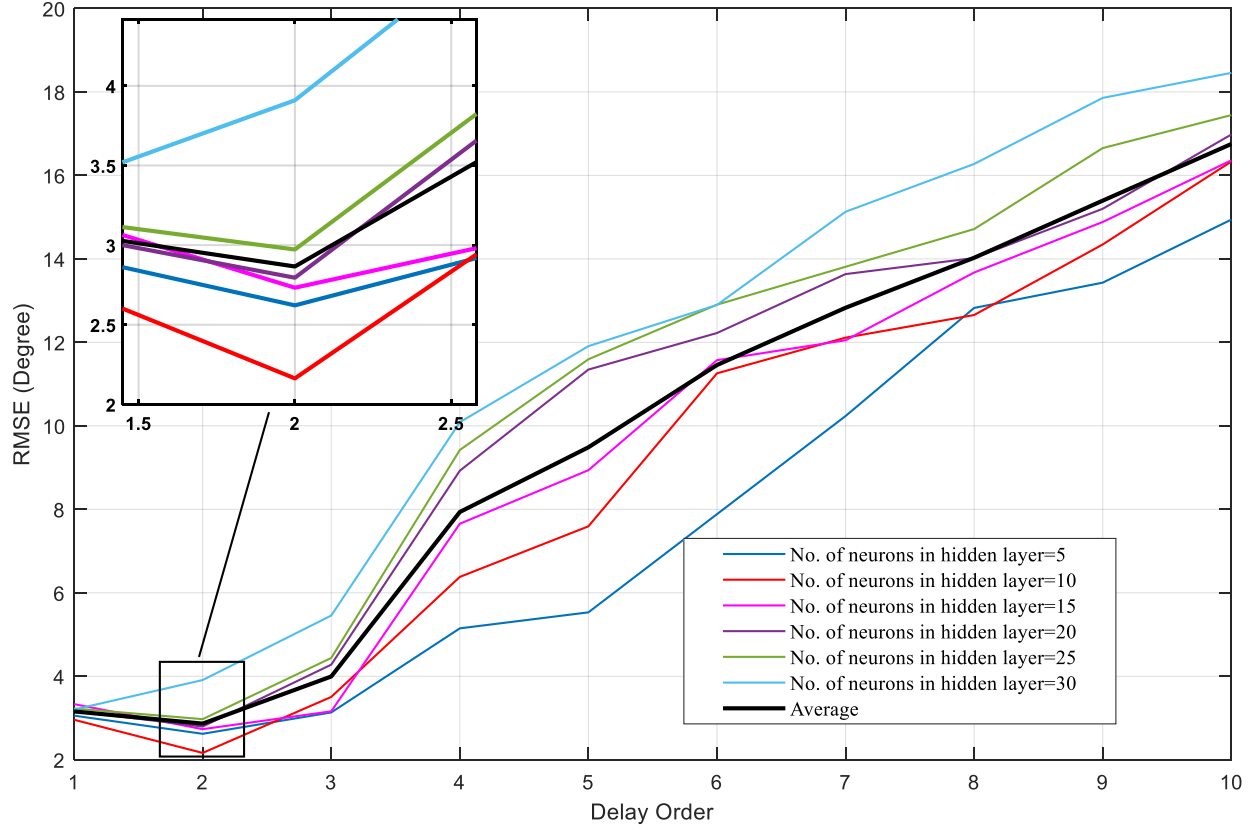


Figure 5.4 RMSE for different NARX parameters

The performance of the NARX model is highly dependent on the number of inputs (delays or model order, m) fed to the network and its structure. The redundant input information results in network vibration and unstable output. The number of hidden layer neurons directly affects the complexity and performance of the model. In the presented research work, the performance of the NARX model has been accessed for various combinations of model order and the number of neurons in the hidden layer. Figure 5.4 shows the RMSE of the NARX model for LW activity. It has been observed that the model performance decreases as the order of the model increases. Whereas, an increase in the number of neurons in hidden layers does not affect the performance much. The minimum RMSE has been achieved with model order 2 and 10 neurons in hidden layers. Further, an increase in the number of neurons directly increases the training time of the model. Results show that the optimal number of neurons and model order comes out as 10 and 2, respectively. With model order 2 ($m=2$), the number of neurons in the input layer will be 8, *i.e.*, 3 input and 1 output feedback with order 2. The same parameters of the NARX model have been used for further analysis.

Table 5.1 Joint angle estimation error (RMSE in degree) for all subjects

Subject	Locomotion				
	LW	SA	SD	RA	RD
S1E2	2.04 ± 0.33	2.83 ± 0.64	2.99 ± 0.71	3.93 ± 0.80	3.70 ± 0.60
S2E2	2.21 ± 0.30	3.18 ± 0.48	2.50 ± 0.57	3.73 ± 0.78	3.62 ± 0.34
S3E2	2.47 ± 0.46	3.38 ± 0.45	3.04 ± 0.74	3.92 ± 0.67	3.81 ± 0.47
S4E2	2.45 ± 0.54	3.13 ± 0.49	2.62 ± 0.73	3.68 ± 0.57	3.91 ± 0.68
S5E2	2.05 ± 0.20	2.74 ± 0.43	3.16 ± 0.68	3.96 ± 0.84	2.84 ± 0.57
S6E2	2.16 ± 0.54	3.01 ± 0.66	2.62 ± 0.55	3.69 ± 0.63	4.18 ± 0.75
S7E2	2.87 ± 0.40	2.77 ± 0.55	2.66 ± 0.76	3.15 ± 0.36	3.93 ± 0.51
S8E2	2.03 ± 0.32	3.12 ± 0.46	2.96 ± 0.69	2.98 ± 0.45	3.90 ± 0.82
S9E2	2.05 ± 0.20	2.84 ± 0.49	3.16 ± 0.68	3.36 ± 0.43	3.84 ± 0.61
S10E2	2.42 ± 0.49	2.92 ± 0.53	3.06 ± 0.37	3.68 ± 0.97	3.93 ± 0.42

Table 5.2 CCoef between actual and estimated joint angle for all subjects

Subject	Locomotion				
	LW	SA	SD	RA	RD
S1E2	0.981 ± 0.005	0.976 ± 0.010	0.977 ± 0.008	0.973 ± 0.011	0.969 ± 0.010
S2E2	0.988 ± 0.002	0.967 ± 0.017	0.978 ± 0.007	0.973 ± 0.005	0.973 ± 0.010
S3E2	0.980 ± 0.003	0.973 ± 0.014	0.977 ± 0.007	0.970 ± 0.008	0.963 ± 0.012
S4E2	0.979 ± 0.008	0.969 ± 0.014	0.973 ± 0.006	0.970 ± 0.013	0.965 ± 0.009
S5E2	0.984 ± 0.005	0.962 ± 0.014	0.972 ± 0.007	0.969 ± 0.014	0.972 ± 0.010
S6E2	0.986 ± 0.004	0.970 ± 0.014	0.976 ± 0.006	0.975 ± 0.006	0.967 ± 0.010
S7E2	0.976 ± 0.010	0.974 ± 0.011	0.970 ± 0.010	0.964 ± 0.012	0.962 ± 0.008
S8E2	0.971 ± 0.007	0.972 ± 0.013	0.978 ± 0.004	0.968 ± 0.014	0.969 ± 0.013
S9E2	0.983 ± 0.003	0.973 ± 0.008	0.968 ± 0.010	0.972 ± 0.014	0.972 ± 0.010
S10E2	0.970 ± 0.007	0.968 ± 0.009	0.978 ± 0.005	0.966 ± 0.013	0.968 ± 0.014

The individual NARX model has been developed for each locomotion. LOOCV scheme has been adopted to access the performance of the model, *i.e.*, nine trials have been used for training and one for testing. Table 5.1 and Table 5.2 presents the ankle joint angle estimation RMSE and CCoef for all ten subjects for different locomotion. Among all subjects, the RMSE has been found in the range of 2.03°-2.87° for LW locomotion, whereas for SA and SD locomotion it has been found in the range of 2.74°-3.38° and 2.62°-3.16°, respectively. Further, for RA and RD locomotion, it varies in the range of 2.98°-3.96° and 2.84°-4.18°. The variation in CCoef, for LW locomotion,

has been found in the range of 0.971-0.988. Whereas, for SA and SD, it has been found in the range of 0.962-0.978 and 0.968-0.978, respectively. Further, for RA and RD locomotion, it varies in the range of 0.964-0.973 and 0.962-0.973. RMSE and CCoef signify the accuracy and consistency of joint angle estimation. The developed ankle joint angle estimation module results for LW locomotion has shown better performance as compared to other locomotion.

Figure 5.5 shows the average RMSE and CCoef for each locomotion. The average RMSE and CCoef of subjects, for LW locomotion, has been found $2.30 \pm 0.59^\circ$ and 0.980 ± 0.008 , whereas for SA, SD, RA and RD locomotion it is $3.00 \pm 0.56^\circ$ and 0.97 ± 0.013 , $2.88 \pm 0.70^\circ$ and 0.975 ± 0.008 , $3.61 \pm 0.75^\circ$ and 0.970 ± 0.012 , $3.87 \pm 0.61^\circ$ and 0.968 ± 0.011 , respectively. However, the average RMSE of all locomotion is found in the range of 2.30 to 3.87 and CCoef as 0.968 to 0.980. Figure 5.6 shows the actual and estimated ankle joint angle of subject 1 for all five activities. It helps in identifying the major events of errors in ankle joint angle estimation. The results show that apart from the lower and upper RoM limit, the model seamlessly estimates the ankle joint angle. Major events of the error have been near the upper and lower limit (peaks) of the joint angle.

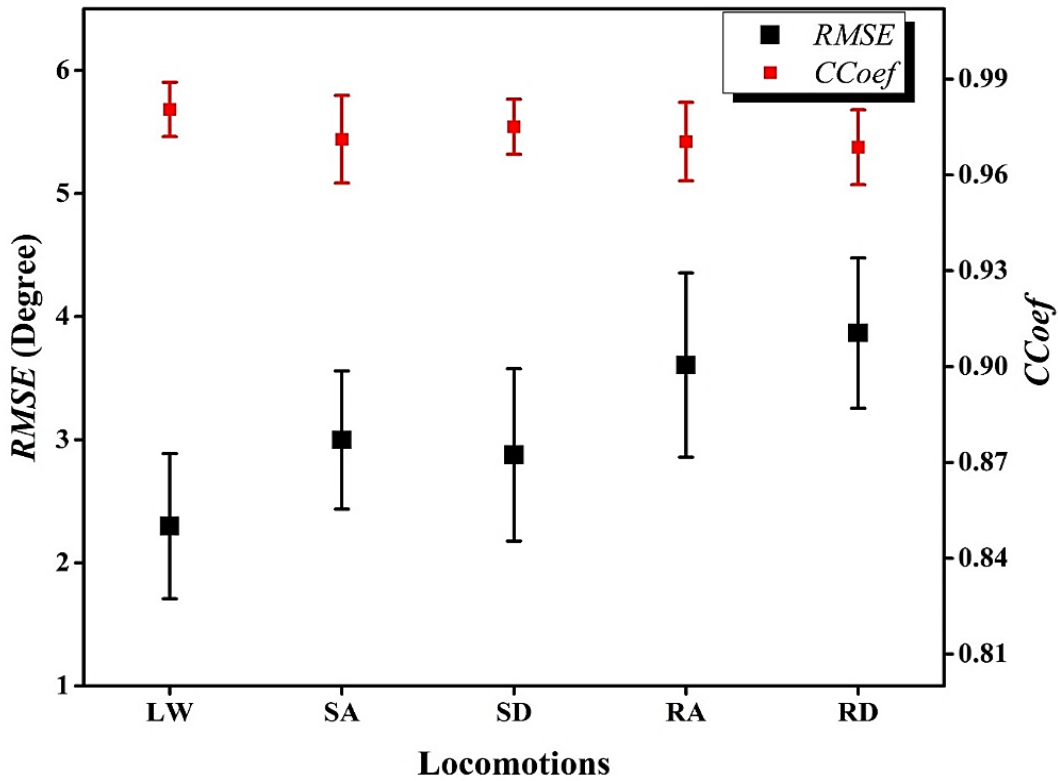


Figure 5.5 Average RMSE and CCoef for different locomotion

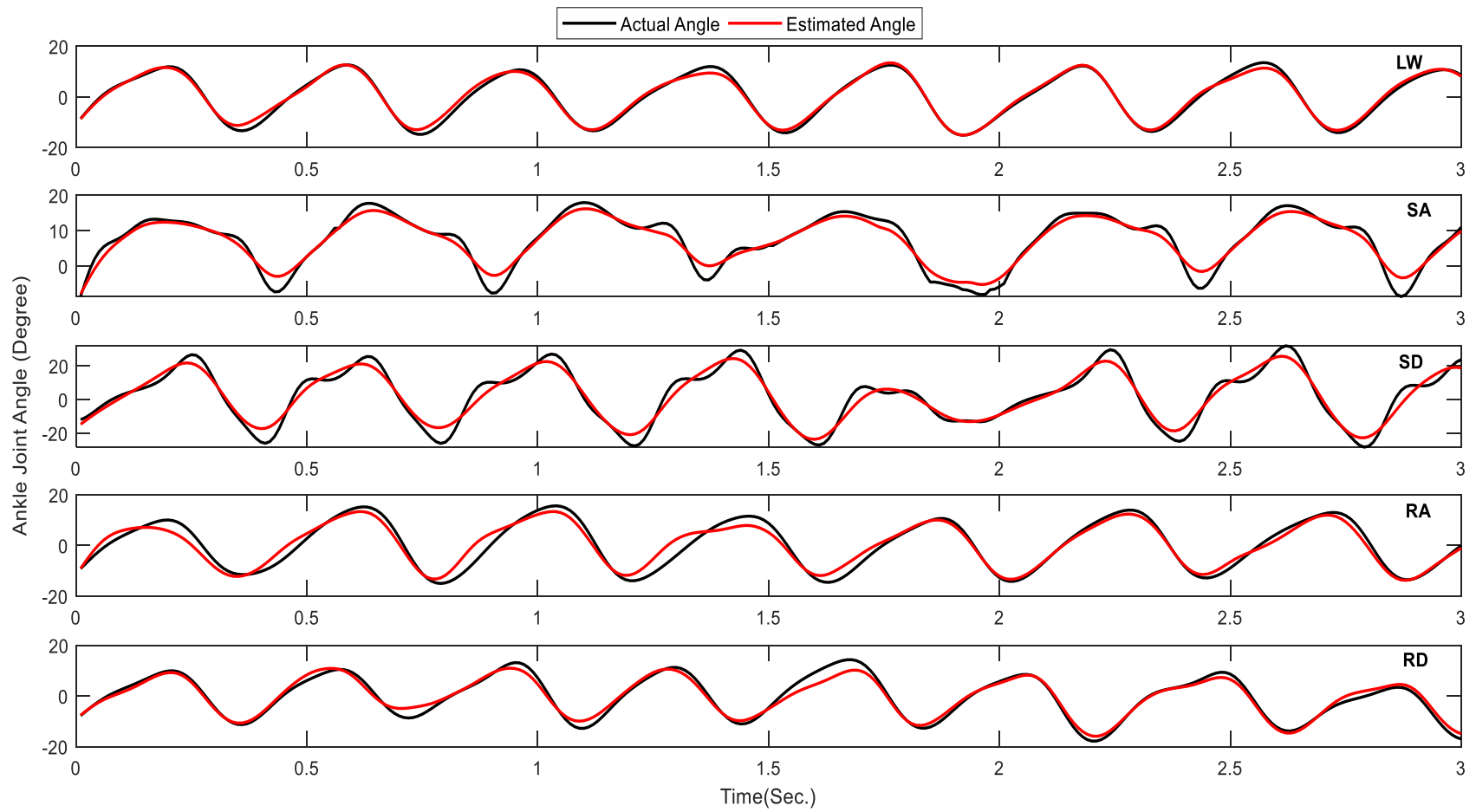
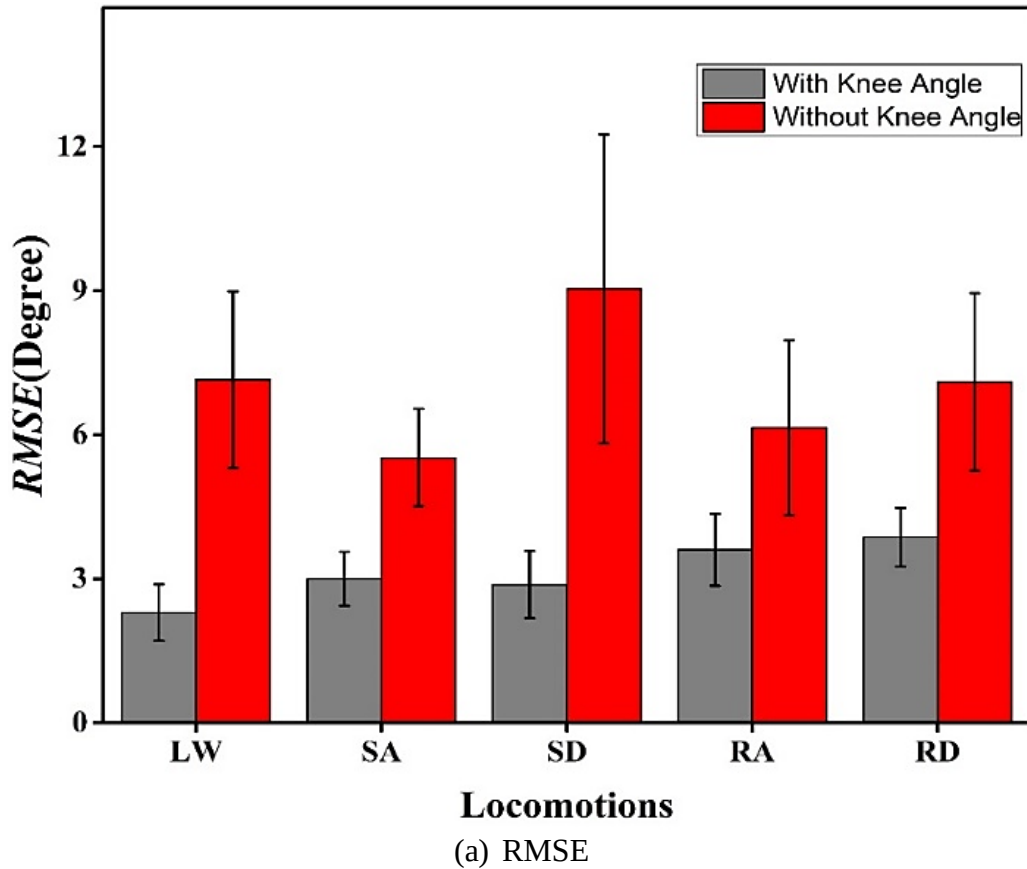


Figure 5.6 Actual and estimated ankle joint angle for different locomotion

Figure 5.7 shows the average performance of the proposed model with and without knee angle information. It has been observed that model performance improves significantly (One-way ANOVA, $p\text{-value} < 0.05$) by incorporating knee angle information as an input. In terms of ankle joint angle estimation accuracy (*i.e.*, RMSE) an improvement of 67.85%, 45.74%, 68.17%, 41.35%, and 45.56% has been observed for LW, SA, SD, RA and RD activity, respectively. Whereas, the consistency of ankle joint angle estimation (CCoef) has shown enhancement of 36.19%, 57.82%, 68.24%, 22.34% and 49.05% for LW, SA, SD, RA and RD activity, respectively. The inclusion of the KA signal for ankle joint angle estimation contributes to model accuracy as well as reliability. Also, by including KA as an input within-subject performance variation has been reduced significantly for all activities. The continuous predictive capability of the model can provide a more biomimetic ankle motion. The performance of the proposed method has been examined to continuously map ankle joint angles across for five locomotion (LW, RA, RD, SA, and SD). The results have been found consistent for all locomotion, which makes it suitable for control of the active ankle-foot prosthesis.



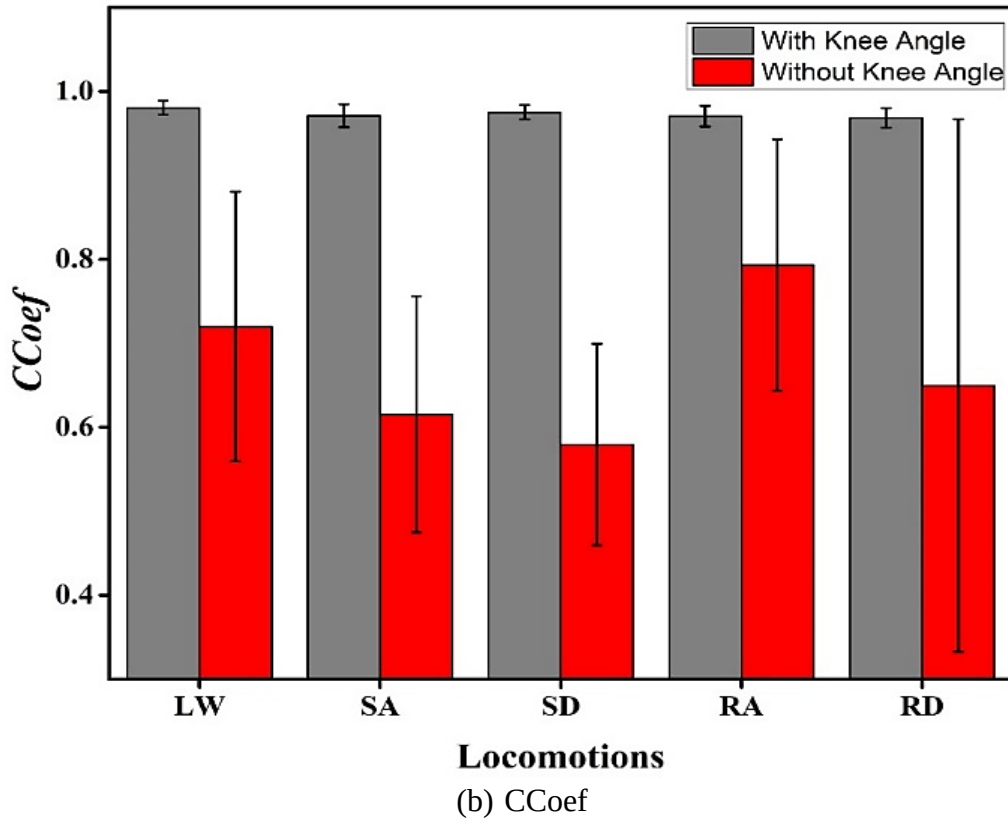


Figure 5.7 Performance measures for with KA and without KA information

5.2 Prosthesis Prototype and Control Sequence

The prosthesis prototype has been developed in the laboratory and operated through predicted ankle joint angles for different locomotion. Figure 5.8 shows the ankle-foot prosthesis prototype. It has one-DoF with an active DF/PF ankle-foot movement. The prototype structure has been designed using aluminum angle bars. It has several advantages, like, lightweight, cost effective, easy for machining in the laboratory environment, and availability. However, for actual working prosthesis, carbon fiber can be preferred because of its high stiffness and strength. The prototype structure consists of a linear electric actuator and a control circuit. Figure 5.9 depicts the internal components of the linear actuator used in the prosthesis prototype. It has four major parts; DC motor, gear assembly, lead screw, and limit switches. The gear assembly is provided to generate high-torque, and the lead screw converts the angular motion of the DC motor into linear movement. Two limit switches provide safety by preventing any accidental hyper-DF/PF. The actuator is able to generate holding torque of 1500 N with operating voltage 12 V and current <2 Amp [159]. The linear stroke length of the actuator is 10 cm. The RoM of DF and PF for a normal human is in the

range of 20° and 50° , respectively. The total RoM of the designed prototype is 70° , whereas the neutral position (during standing) of the ankle-foot has been kept at the stroke length of 3 cm. so that the complete RoM for both DF and PF must be covered. The total weight of the developed prototype is 1.5 Kg. A shoe insole has been used to provide cushioning during the stance phase and shock tolerance while heel contact.

The control circuit of the prototype has three major parts; microcontroller and motor driver and power supply. ATmega328p microcontroller has been used to generate the control signal. A dual H-Bridge motor driver IC L298N has been used to drive the actuator. The H-bridge motor driver provides control over the speed and direction of the actuator. The microcontroller generates the control signal as per the current and desired ankle-foot angle, which further transmits to the motor driver that drives the actuator. The microcontroller and motor driver both work on 5V DC supply, whereas the actuator requires 12V DC supply. So, two separate DC supply, one of 5V for microcontroller and motor driver, and one of 12V for actuator have been used.

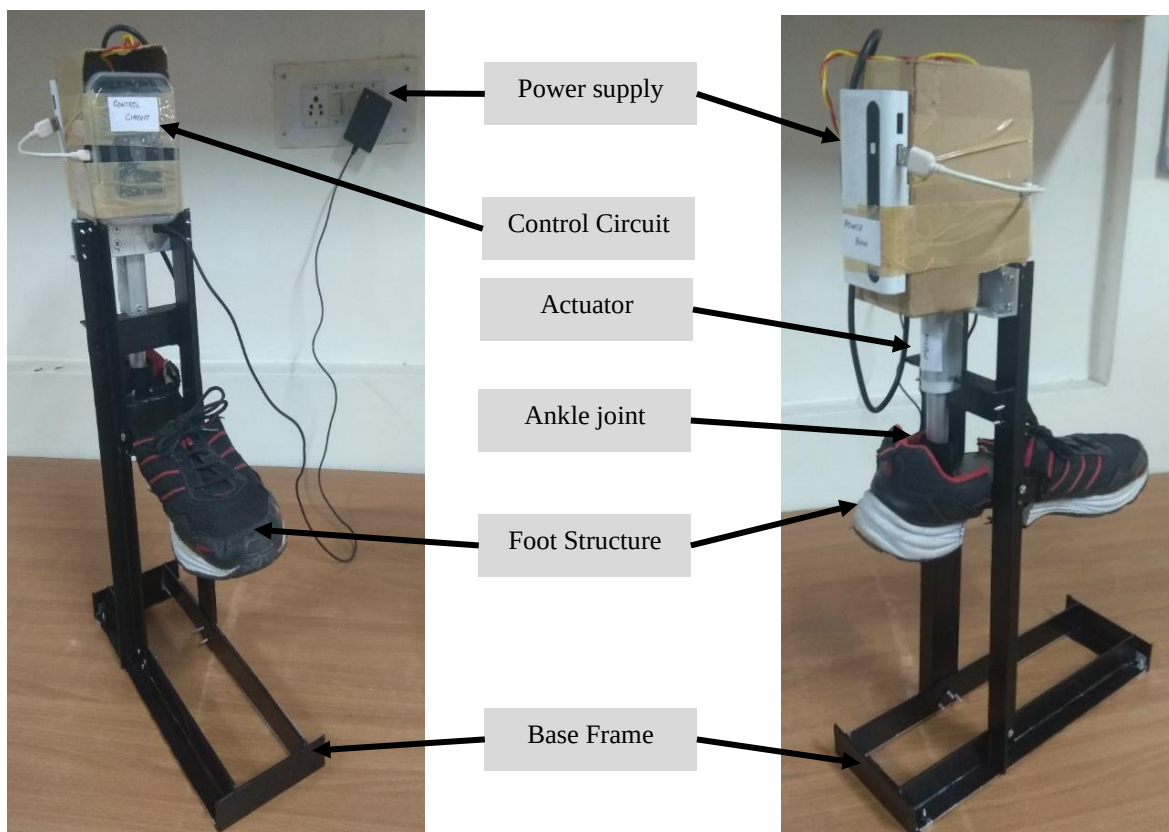


Figure 5.8 Design of an ankle-foot prosthesis prototype

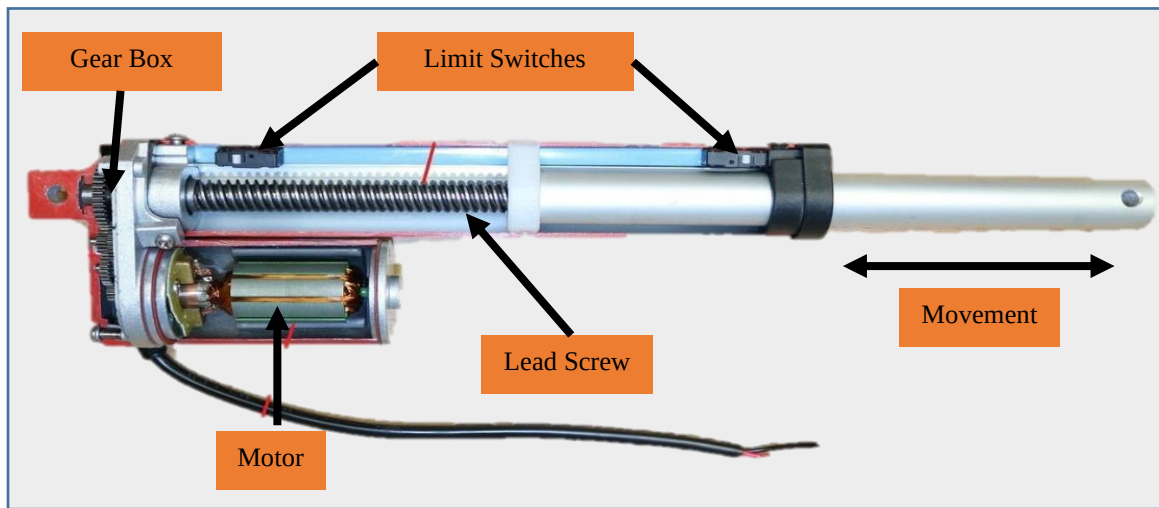


Figure 5.9 Internal components of linear actuator used in prosthesis prototype

Figure 5.10 shows the control sequence used to operate the prototype. When the prosthesis gets switched-on, it will initialize the ankle-foot angular position, *i.e.*, ankle joint angle, while the subject is STD. Simultaneously, the activity and locomotion prediction module (explained in section 4.2) also starts. Its level-1 classification stage continuously checks for the subject activity as per his/her EMG and KA signal, and if the subject is STD, the ankle-foot angular position will remain same at its initial position, otherwise (*i.e.*, WLK activity has been identified), level-2 classification stage get activated. In this stage of classification, the EMG and KA signal has been segmented into subwindows, as per the gait events (WAH, WBT, WAT, and WBH), and respective classifier has been triggered. Level-2 classification stage predicts the locomotion of the subject (LW, RA, RD, SA, SD, and STD), and this information is transmitted to the ankle joint angle estimation module (explained in section 5.1). If the predicted locomotion is STD, the ankle-foot prosthesis will come to its initial angular position, and the level-1 classification stage of activity/locomotion prediction module continuously checks for the subject activity again. However, if the predicted locomotion is other than STD, the angle estimation module estimates the angular position of ankle-foot as per the locomotion using EMG and KA signal information. The developed prototype has been operated offline for different locomotion. The estimated ankle joint angle information has been passed to the microcontroller, which generates a control signal to actuate the prosthesis prototype.

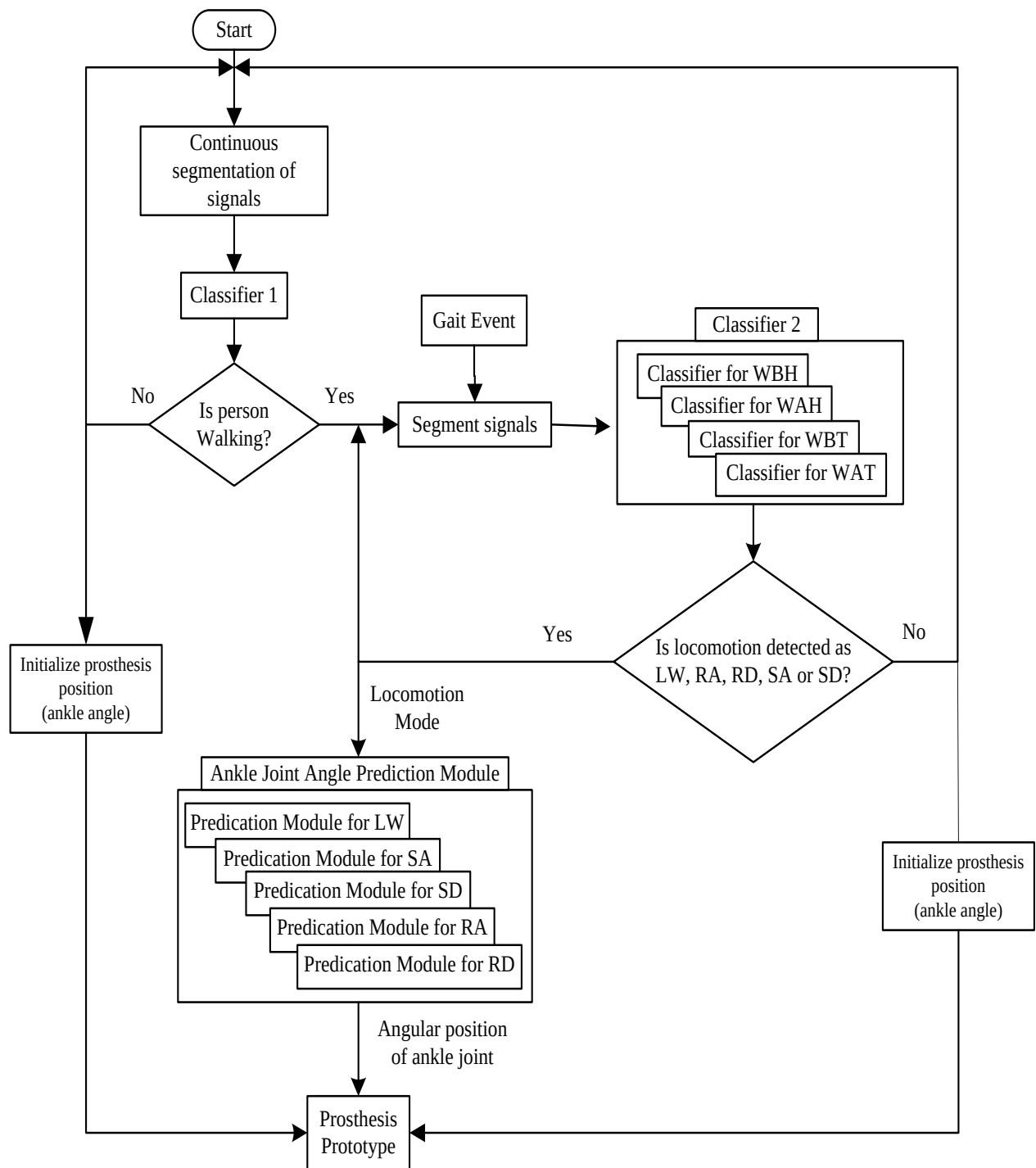


Figure 5.10 Control sequence of prosthesis prototype

In this chapter an NARX model-based ankle joint angle estimation algorithm has been developed which continuously estimate the ankle joint angle using KA signal in addition with EMG signal of two lower limb below-knee muscles (TiAn and Gast). The performance (RMSE and CCoef) of proposed method has been analysed on dataset of ten subjects for five daily life locomotion (LW, SA, SD, RA and RD). The average RMSE and CCoef have been found in the range of 2.30°-3.87° and 0.968-0.980. Moreover, it has been observed that addition of KA signal improved the performance of model significantly. Further, an electric actuator operated ankle-foot prosthesis prototype has been developed. The developed prototype has one-DoF providing DF/PF ankle-foot movement, and operated successfully in offline mode using estimated ankle joint angle.

Chapter 6

Conclusions and Future Scope

6.1 Conclusions

Lower limb amputation is one of the most frequent types of amputation around the world. The below-knee (transtibial) amputation is more prominent among lower limb amputation. The metabolic energy required for regular walking activity has been increased by 40-50% for a transtibial amputee. A transtibial amputee has to dedicate more cognitive effort in performing daily life locomotion. Moreover, their locomotion is very slow and unstable. An ankle-foot prosthesis is an artificial limb that can upgrade and deal with the daily life activities life by replacing the function of the missing limb. An effective ankle-foot prosthesis should address these clinical issues and provide seamless operation of prostheses. Most of the commonly used ankle-foot prostheses are passive or trigger control. These prostheses are not able to provide required push-off during locomotion, and also continuous attention of amputees is needed. These drawbacks can be overcome by active ankle-foot prostheses and including subject locomotion intention within the control sequence of prostheses. Myoelectric control of prosthesis promises the natural appearance of the ankle-foot with effective functionality. The presented research work developed a hybrid ankle-foot prosthesis prototype with, one-DoF, active DF/PF movement.

The human lower limb musculoskeletal structure is redundant. It is imperative to investigate the EMG signal of muscles before recruiting them for HMI. The presented research work had evaluated the performance of below-knee muscles for different ankle-foot movements. The performance of muscles had been compared on the ground of their activation level, activation duration, and fatigue for repetitive weight bearing (PFW/DFW) and non-weight bearing ankle movements (PF/DF). Out of six compared muscles, TiAn and Gast had been found suitable for compared ankle-foot movements.

Further, to achieve seamless operation of the prosthesis, an activity and locomotion prediction module had been designed and tested on the data set of ten subjects. The activity and locomotion identification module acted as a high-level controller for the prosthesis. A two-level classification approach had been implemented for activity and locomotion prediction. In the first level, STD and WLK activity had been identified using EMG signals of four lower limb muscles (TiAn, Gast,

VaLa, and BiFe) and KA signal. The performances of three classifiers (LDA, SVM, and NN) had been compared. The average % classification accuracy for LDA, SVM, and NN classifiers had been found as $99.07 \pm 0.64\%$, $98.84 \pm 0.41\%$, and $98.89 \pm 0.46\%$ (One-way ANOVA, p -value >0.05). The second level of classification worked only if in first level WLK activity was identified. It had been used to predicted five steady locomotion modes (LW, SA, SD, RA, RD) and nine locomotion transitions ($LW \leftrightarrow SA/SD$, $LW \leftrightarrow RA/RD$, and $LW \rightarrow STD$). In this level, a phase-dependent classification approach had been implemented. Four subwindows (WAH, WBT, WAT, and WBH) over a complete gait cycle were extracted, and for each subwindow, an individual classifier had been trained and tested using hybrid (EMG and KA signal) information. In the case of steady-state locomotion mode prediction, an average % classification accuracy of $97.21 \pm 0.78\%$, $95.43 \pm 1.61\%$, and $94.61 \pm 1.59\%$ had been depicted by LDA, SVM and NN classifiers (One-way ANOVA, p -value <0.05). Whereas, % of missed locomotion transition had been found as 5.11%, 8.78%, and 8.89% for LDA, SVM and NN classifiers (One-way ANOVA, p -value <0.05). The optimal size for each subwindow was found 200 msec, and a group of muscle having four muscles (TiAn, Gast, VaLa, and BiFe) was found appropriate for locomotion prediction. Further, the LDA classifier with hybrid information (EMG+KA signal) had depicted better performance for steady-state locomotion and locomotion transition prediction. Moreover, the LDA classifier is also considered as computationally less expensive. Hence, it had been preferred over other compared classifiers for activity and locomotion prediction.

Thereafter, an ankle joint angular position estimation module had been developed to control the ankle-foot prosthesis. It utilized the EMG signal of two lower limb below-knee muscles (TiAn and Gast) along with the KA signal. NARX neural network had been used as the learning model for angle estimation. An individual NARX model has been trained and tested for individual locomotion (LW, SA, SD, RA, and RD). The results showed that, for LW activity, the average RMSE and CCoef came out as $2.30 \pm 0.59^\circ$ and 0.980 ± 0.008 , whereas for SA, SD, RA, and RD locomotion it was $3.00 \pm 0.56^\circ$ and 0.97 ± 0.013 , $2.88 \pm 0.70^\circ$ and 0.975 ± 0.008 , $3.61 \pm 0.75^\circ$ and 0.970 ± 0.012 , $3.87 \pm 0.61^\circ$ and 0.968 ± 0.011 , respectively. NARX model with EMG and KA information proved its efficacy for continuous estimation of ankle-foot joint angle. The continuous joint angle estimation property of the developed model facilitated better control and seamless operation of the prosthesis. Further, an electric actuator-based laboratory prototype of an ankle-

foot prosthesis, with active DF/PF movement, had been developed and operated using the estimated ankle joint angle.

6.2 Future Scope

As future work, the following suggestions are made to improve the performance of proposed prosthesis:

- High-density EMG (HDEMG) signal may provide better muscle activation information in the spatial domain which can improve the overall performance of the prosthesis
- The hardware-based machine learning system composed of the electronic representation of the output of classifier in online mode can be designed for motion recognition
- The performance of the developed prosthesis prototype can be analyzed for transtibial amputee subject by involving medical practitioner and trained prosthetist in the research
- The mechanical structure design can be optimized by using computer-aided designs, and advanced electric actuators can be used to improve the performance of the prosthesis
- The prosthesis structure can be fabricated using a 3D printing technique using low weight fiber material.

List of Publications

Journal Publications

- **Rohit Gupta**, I. S. Dhindsa and Ravinder Agarwal, Continuous angular position estimation of human ankle during unconstrained locomotion, *Biomedical Signal Processing and Control*, Elsevier, vol. 60, 2020. **DOI: 10.1016/j.bspc.2020.101968**
- **Rohit Gupta** and Ravinder Agarwal, Single channel EMG-based continuous terrain identification with simple classifier for lower limb prosthesis, *Biocybernetics and Biomedical Engineering*, Elsevier, vol. 39, no. 3, pp. 775–788, 2019
- **Rohit Gupta** and Ravinder Agarwal, Electromyographic Signal-Driven Continuous Locomotion Mode Identification Module Design for Lower Limb Prosthesis Control, *Arabian Journal for Science and Engineering*, Springer, vol. 43, no. 12, pp. 7817–7835, 2018
- **Rohit Gupta** and Ravinder Agarwal, Single Muscle Surface EMGs Locomotion Identification Module for Prosthesis Control, *Neurophysiology*, Springer, vol. 51, no. 3, pp.191–208, 2019
- **Rohit Gupta** and Ravinder Agarwal, Continuous human locomotion identification for lower limb prosthesis control, *CSI Transactions on ICT*, Springer, vol. 6, no. 1, pp. 17–31, 2018
- **Rohit Gupta** and Ravinder Agarwal, sEMG Interface Design for Locomotion Identification, *International Journal of Electrical and Computer Engineering*, WASET, vol. 11, no. 2, pp. 66–75, 2017

Papers presented in National and International Conferences

- **Rohit Gupta** and Ravinder Agarwal, Lower limb muscle EMG analysis to predict ankle-foot activities for prosthesis control, *International Conference On Smart Machine Intelligence and Real-Time Computing* (SMART COM 2020), June 26-27, 2020, Pauri, Uttarakhand
- **Rohit Gupta** and Ravinder Agarwal, Feature Reduction and selection of SEMG signal for locomotion identification, 9th *International Conference on Advances in Metrology* [AdMet 2016], February 23-26, 2016, National Physical Laboratory, New Delhi
- **Rohit Gupta** and Ravinder Agarwal, Roadmap to Low Cost Electronically Operated Prosthetic Limbs, *India International Science Festival 2016 (IISF 2016)*, 07-11 Dec., 2016, CSIR-NPL, New Delhi
- Abhinandan Aggarwal, **Rohit Gupta** and Ravinder Agarwal, Design and Development of Integrated Insole System for Gait Analysis, 11th *IEEE International Conference International Conference on Contemporary Computing (IC3)*, August 2-4, 2018, Noida. [10.1109/IC3.2018.8530543]

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