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Implementation of AI based approach for disturbance estimation of a MIMO nonlinear system

Masters of Science in Electrical Engineering

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Dedication

I dedicate this small Piece of the effort to my parents supervisor as well as my colleagues, who encouraged and supported me during the whole tenure. Without their support and sincere advise, it could not possible to complete within a given time period.

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Abstract

Postural control is the ability to maintain equilibrium by keeping or returning the center of gravity (COG) over its base of support (BOS), and it relates to how the body's position in space controls for stability. The center of gravity (COG) is a point at which all an object's mass can be concentrated in relation to gravity. The postural control system serves as a feedback control circuit between the brain and the musculoskeletal system. The internal dynamics of a system model are one of the major functional components that the posture control system relies on. So, the modeling of CNS will be represented by an extended high gain observer (EHGO) which is based on a feedback linearization controller. Basically, EHGO works as a disturbance estimator and a soft sensor of the internal dynamics, respectively. Moreover, AI approach contributes to a better knowledge of the postural control and STS mechanism. Second part of this research focus on traditional machine learning approach used to improve robotic and exoskeleton design. By using head positions of different experimental objects, regression model will predict the positions of ankle, knee, and hip joints. Therefore, on head positions defined as input and position of joints are outputs of the model. In this research supervised learning is used because inputs and outputs are defined or known. So, the techniques used under supervised learning are random forest regression, support vector regression (SVM), decision tree regression.

Contents

Abstract	vi
1 Introduction	1
1.1 Introduction	1
1.2 Control Theory	1
1.2.1 Linear Control Theory	2
1.2.2 Nonlinear Control Theory	2
1.3 Nonlinear Control of MIMO Systems	2
1.4 Human Movement for a biomechanical perspective	3
1.5 Posture Movements	3
1.6 Posture Control	4
1.7 Machine Learning	4
1.8 The Research Gaps	4
1.9 The Research Objectives	5
1.10 Thesis outline	5
2 Literature Review	7
2.1 Posture Motion	7
2.2 Posture Balance	8
2.2.1 Central Nervous System (CNS)	8
2.2.2 Center of Mass (CoM)	9
2.2.3 Limitation of Posture Stability	9
2.3 Biomechanical movement	9
2.4 Posture movement	10
2.5 Biomechanical Model	10
2.6 Non-Linear Control system	11
2.7 Posture Control Model	11
2.8 Artificial Intelligence	12
2.8.1 Machine Learning	12
2.8.2 Deep Learning	13
2.9 Types of Learning	14
2.9.1 Supervised Learning	14
2.9.2 Unsupervised Learning	15
2.9.3 Reinforcement Learning	15
2.10 Data Collection	15
2.10.1 Structuring the Data	16
2.10.2 Data Processing	16

3	Experimental data validation & analysis through machine learning approaches	17
3.1	Experiment Apparatus	17
3.2	Subjects for Experiment	17
3.3	Equipment and Calibration	18
3.4	Challenges during Experiment	18
3.4.1	Set of Protocols	18
3.5	Motion Capture	19
3.6	Infra-Red Cameras	20
3.7	Data Acquisition and Motive Screen	20
3.8	Force Capture	20
3.9	Mocap Toolbox	22
3.9.1	Reading and plotting the MoCap Data	22
3.9.2	Motion Data Analysis	23
3.10	Machine Learning Approach	24
3.10.1	Support Vector Regression	25
3.10.2	Decision Tree Regression	26
3.10.3	Random Forest Regression	29
4	Postural Stability of a Single Link Model	34
4.1	Non-Linear Biomechanical model	34
4.2	Extended High Gain Observer Design	36
4.3	Nonlinear Compensator	38
4.4	Simulations Results	38
5	Conclusions & Future work	43
5.1	Conclusion	43
5.2	Future Work	43
A	Turnitin Originality Report	50

List of Figures

1.1	MIMO System	3
1.2	Workflow of machine learning	5
2.1	Types of AI	13
2.2	Perceptron	14
2.3	Representation of a neuron	14
2.4	Actual output with desired output	15
3.1	Motion capture workflow	19
3.2	Infra-Red Optitrack Camera and Optihub	20
3.3	Experimental setup	21
3.4	Optitrack Motive software Interface	21
3.5	Experimental setup for force capture	21
3.6	Pasco force plate and 850 universal interface	22
3.7	Data acquisition and data analysis	22
3.8	Animation in marker space	23
3.9	Join Markers	23
3.10	Motion Capture and data validation	24
3.11	Neural Network Model	25
3.12	Python interface using Support Vector Regression	26
3.13	Trained and predicted data set of Ankle joint	27
3.14	Trained and predicted data set of Knee joint	27
3.15	Trained and predicted data set of Hip joint	28
3.16	Python interface using Decision Tree Regression	28
3.17	Trained and predicted data set of Ankle joint	29
3.18	Trained and predicted data set of Knee joint	30
3.19	Trained and predicted data set of Hip joint	30
3.20	Python interface using Random Forest Regression	31
3.21	Trained and predicted data set of Ankle joint	32
3.22	Trained and predicted data set of Knee joint	32
3.23	Trained and predicted data set of Hip joint	33
3.24	Comparison of previous and applied techniques	33
4.1	Segment Model	35
4.2	Parameters with values	35
4.3	Model Implementation in MATLAB SIMULINK	38
4.4	Angular Positions at Ankle joint with respect to time	39
4.5	Angular Velocity at Ankle joint with respect to time	39

4.6	Ankle joint torque with respect to time	40
4.7	Ground reaction forces (GRF)	40
4.8	Angular Positions of ankle joint with delays	41
4.9	Angular Velocities of ankle joint with delays	41
4.10	Ankle Joint Torques with delays	42
4.11	Comparison	42

Acronyms and Abbreviations

AI	Artificial Intelligence
ML	Machine Learning
MIMO	Multi-Input Multi-Output
SVM	Support Vector Machine
ANN	Artificial Neural Network
STS	Sit to stand
COM	Center of Mass
ANFIS	Adaptive Neural Fuzzy Interface System

Chapter 1

Introduction

1.1 Introduction

In our daily most of activities require posture and balance, which are neither exactly equivalent nor separate. Understanding the challenge of postural control is necessary to comprehend a person's postural behavior. A feedback control circuit connects the brain and the musculoskeletal system through the posture control system. Postural control, which is related to how the body's position in space controls for stability, is the capacity to maintain equilibrium by retaining or bringing the center of gravity (COG) over its base of support (BOS). The center of gravity (COG) is a point at which all an object's mass can be concentrated in relation to gravity. The internal dynamics of a system model are one of the major functional components that the posture control system relies on. Furthermore, the system inputs and the synchronization of motor strategies. Feedback from the sensory system sends commands to the extremity muscles, who then contract appropriately to maintain postural stability.

1.2 Control Theory

Control theory is the important branch of engineering deals with the behavior of system dynamics which include input and output parameters. So, in control theory system output is modified by changing input by using feedback and feedforwarding methods and a system which is to be controlled is know as Plant. Basically, control theory is divided into two types which are,

- Linear control theory
- Nonlinear control theory

1.2.1 Linear Control Theory

Linear control theory is applicable on a system which obey superposition principle which governed by linear differential equations. Although, parameters of Linear systems do not change with time commonly known as Linear time invariant (LTI) systems. So, the mathematical techniques which are used to simplify linear differential equations are Laplace transform, Root locus, Bode plot and Nyquist criterion.

1.2.2 Nonlinear Control Theory

Nonlinear control deals with the systems which are nonlinear and time variant or both. Nonlinear control theory is applicable on a system that do not obey superposition principle which governed by nonlinear differential equations. Although, nonlinear control is mostly applying on real-time/non-Ideal systems because all real control systems are nonlinear in nature. The mathematical methods that have been created to handle nonlinear differential equations are more precise and less universal, frequently applicable to specific types of systems. So, there are some theories through which stability factor of nonlinear systems are described which include limit cycle theory, Lyapunov stability theory and describing functions. Nonlinear controllers have simpler implementation, faster speed, more accuracy, or reduced control energy, which justify the more difficult design procedure. Generally, linear mathematics is used to develop the biomechanical analysis of human movement. While these methods are effective in a variety of contexts but do not adequately capture the behaviour of the human body systems that are primarily nonlinear in nature.

1.3 Nonlinear Control of MIMO Systems

Multi-input Multi-output (MIMO) theory deals with the system that have complex dynamics having multiple input variables that regulate several output variables. Basically, MIMO system is a group of standalone or connected single-input single-output (SISO) subsystems that can be conditionally represented as a single entity.

The primary characteristics and challenges of MIMO control are typically tied primarily to the high dimensions of the plant models. The same approaches used to solve SISO control problems like regulation and tracking control of MIMO systems, however the resulting controllers are far more complicated and less useful. When the system may be represented as a group of weakly connected or non-interacting pieces, simplification is achievable. Additionally, if the primary control problem is decompose into a number of independent problems, therefore separate controllers with a more straightforward structure for each subsystem are used and verify, as necessary, that the resulting closed loop system complies with the standard requirements for control processes.

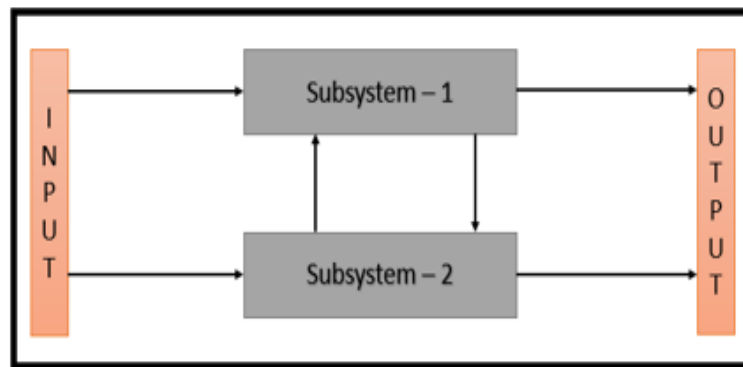


Figure 1.1: MIMO System

1.4 Human Movement for a biomechanical perspective

The study of motion in biological systems is called biomechanics. Basically, the word biomechanics is a combination of biology and mechanics, where the application of the laws of physics and the laws of mechanics, on biological systems are studied. Motion biomechanics is the science of motions of the neuro-musculoskeletal system that focus on the role of joints, sensors, bones, muscles, and the central nervous system (CNS). Musculoskeletal systems are usually articulated and hence are modeled as multi-segment machines. In such systems, including the human body there are more joints and muscles than are necessary for performing our daily tasks. Human movement results from a highly complex and coordinated interplay between joints, bones, ligaments, and muscles within the human body which are all controlled by the central nervous system. Muscles generate pulling forces by contracting which results in moments at joints. Besides the joint movements, the 'musculoskeletal system must carry out these movements that ensure the static and dynamic stability of the body since gravitational and other forces are continuously affecting the required motion.

1.5 Posture Movements

Sit to stand (STS) is a motion that every individual executes numerous times a day. It is the preamble to many other movements that are part of activities of daily living like walking or stair climbing. With disease or aging, like other human body movements, STS also deteriorates. An individual's physical independence is ensured if he is capable to perform at least STS. With more percentage of population reaching old age every year throughout the world, it is now more important to give more attention on understanding the STS motion mechanisms, so that problems related with the execution of STS could be better understood and their solutions could be suggested.

1.6 Posture Control

Maintaining balance is regulated by the Central nervous system which depends upon two basic activities which are STS movement and posture stability. So, consider a multiple segment system that contains ankle, knee, and hip joints. Joint torque is an essential need for a body to prevent from balance disorder. So, regulation is required between sensory and CNS against gravity and perturbations to achieve posture stability. Proprioceptor inputs are used by the CNS to produce these torques while accounting for neural transmission delays and joint passive stiffness restrictions. Complex neural control may be impacted by illnesses, ageing people, or process accidents. Therefore, it is crucial to research and comprehend the human motor control system that underlies postural stability. Feedback from the sensory system sends commands to the extremity muscles, who then contract appropriately to maintain postural stability.

1.7 Machine Learning

Since the creation of the computer, we have constantly daydreamed about building artificial intelligence—that is, a system that can think for itself. The capacity to learn and grow as a result of experience is one of the most important characteristics of intelligent behaviour. Although we have the ability to accomplish this since birth, we still do not fully understand how learning actually works. The creation of methods and systems that enable computers to learn the underlying structure of a data collection is the focus of the field of machine learning. In the programme created by a person, this is done with the intention of solving a problem without the need of explicit descriptions. Figure 1.2 depicts the fundamental machine learning workflow.

1.8 The Research Gaps

- The high gain observer (HGO) cannot estimate the states of internal dynamics. However, the nonlinear observers are an important feature of robustness against uncertainties and performance recovery.
- During modeling and analysis of a system nonlinearities are neglected. In common design strategy, the linear control system is to solve the stabilization problems by linearizing the system at valid operating points. The linear approximation design approach is simple and often it works, however, it might impair the original characteristics of the nonlinear system which may lead to an inaccurate or false conclusions.

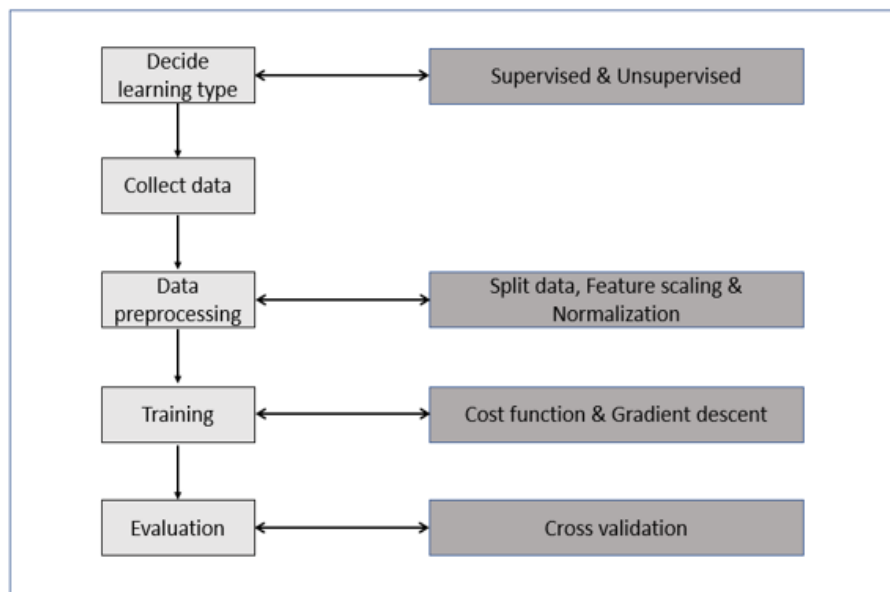


Figure 1.2: Workflow of machine learning

- In postural control system due to psychological structures delays and noises cannot be controlled. So, inaccurate modeling of CNS.

1.9 The Research Objectives

- Consider all the system nonlinearities for analysis and accurate simulations of biomechanical movements.
- Design extended high-gain observer which have capability to estimate disturbances and functions as a soft sensor for internal dynamics.
- Implement AI techniques.

1.10 Thesis outline

The focus of this research is to design a mathematical model to study the postural stability and AI implementation of MIMO system. Also, implement different machine learning technique. The thesis is organized as follow,

- **Chapter-2** covers, Literature review of Posture stability, MIMO nonlinear system, sit to stand movement, Machine learning algorithms, Background of Human Posture.
- **Chapter-3** , designed model, implement extended high gain observer in Simmechanics/Simulink/MATLAB.

- **Chapter-4** present, experimental setup, implement machine learning techniques, result validation.
- **Chapter-5**, discussion, summarized and concluded the research work.

Chapter 2

Literature Review

One of the most essential and fundamental aspects of daily living is the ability to control one's posture in order to maintain an upright stance [1]. Balance maintenance is highly dependent on posture stability [2]. This research focused on nonlinear mathematical model of the musculoskeletal system which produces appropriate movement strategies to execute the plan. This chapter covers important terms which are defined in previous chapter and their importance to the balance recovery during internal or external perturbations, maintaining balance during STS transfer, literature survey of biomechanical models and machine learning techniques.

2.1 Posture Motion

Highly complex and coordinated interplay between joints, bones, ligaments, and muscles within the human body which are all controlled by the central nervous system (CNS). Muscles generate pulling forces by contracting which results in moments at joints. Besides the joint movements, the musculoskeletal system must carry out these movements that ensure the posture stability since gravitational and other forces are continuously affecting the required motion. The interaction of forces within the biological systems as well as with their surroundings received attention from early scholars like Aristotle and Isaac Newton and this list goes on to the researchers of the present day. Their efforts to understand the effect of these mechanical interaction has been evolved into forms a discipline of research called biomechanics [3-5]. The human motion has gone through a long evolutionary process and now it seems that human capabilities to generate finer movements have improved a lot. To predict how a body will move in response to a force is important to be estimated so that movements can be optimized [6]. This knowledge is directly linked with the design and development of devices in every field like sports, orthosis, and

industries. The study of motion in biological system is called biomechanics. Therefore, motion analysis gives a strong basis for studying the causes of diseases and making strategies for their prevention [9]. Musculoskeletal systems are usually articulated and hence are modeled as multi-segment machines. The end effector can approach the target using different combinations of joints angles. This situation is called redundancy. It is an interesting fact that redundancy provides an alternate solution to a movement task in case an injury or disease to the musculoskeletal system makes it difficult or impossible to achieve the target in a normal way [11]. To create a dynamic simulation of some human motion a three-step process is adapted. Muscle torques are calculated then to implement the control and come up with an optimal set of actuation strategies for the forward dynamic simulation that closely matches the experimental results [14]. Applications of human posture stability are human motion has a multitude of relevant applications that have a great social and economical impact. Human motion analysis is the basis of procedures adopted in many domains for example robotics, rehabilitation, and sports etc.

2.2 Posture Balance

One of the most essential and fundamental aspects of daily living is the ability to control one's posture in order to maintain an upright stance [15]. Balance maintenance is highly dependent on posture stability. One of the main causes of injuries globally, especially among the elderly, is falling and losing one's equilibrium. Due to the ageing population, these injuries place burden on public health care resources in many countries across the world [16]. In daily life, posture stability is an important and basic requirement for maintaining balance. Posture stability includes sensory inputs as well as delays [17]. The postural context is controlled by biomechanical variables like body and surface configuration and task objectives like the need to stand still without stepping against the need to quickly regain equilibrium [18]. When perturbations occur, preprogrammed muscle activation patterns can be used to characterise postural responses. The proper reaction is then chosen from a wide range of potential responses [19,20]. A wide range of disturbances to balance can be accommodated by the human posture control system.

2.2.1 Central Nervous System (CNS)

The sensory and central nervous systems (CNS) are necessary for proper posture control, as well as for the human body to respond effectively to forces from gravity and the environment [23]. The entire body must be involved in maintaining proper posture, particularly the lower limbs and trunk [24]. Therefore, based on comparable multisensory signals, the CNS must regulate several muscles at once. The method by which this regulation happens is currently unknown despite the best efforts of researchers due to the

complexity of the CNS. Sensory and vestibular inputs, as well as both proprioceptive and tactile sensory inputs, are used to govern posture-regulating muscles[25,26,27]. Sensory inputs are directly integrated with the body states to generate movements [28]. In this study the fast and slow dynamics are focused on multisensory integration and introduce "internal force control" with multisensory integration-evoked posture adjustment. The research on slow dynamics has lagged that on fast dynamics, making it difficult to identify the underlying mechanisms and develop appropriate models for long-term changes[30].

2.2.2 Center of Mass (CoM)

Various studies also describe the limitations beyond which it is impossible to reestablish the balance. They are expressed in terms of the properties of the disturbance [31], the system's state depends upon position and velocity of the center of mass (CoM), or the moment of the first reaction [32]. However, these thresholds are directly influenced by the events under test, including the types and features of disturbances, instructions, their personal traits, the types of recovery reactions permitted (stepping or not), etc. As a result, it is impossible to utilize them to forecast the result of an untested condition[33-35].

2.2.3 Limitation of Posture Stability

The maximum distance in any direction that an individual can lean away from midline upright position without stepping, grasping, or falling is called stability limit. A hypothetical cone shown in Fig 2.1 can better represent the stability limits. Equilibrium is not a specific position, but an area defined by the size of the BOS and the constraints on joint angles, muscle power, and sensory input which then determine the stability limits [36].

2.3 Biomechanical movement

Recent research studies focus on the neural control of balance mechanism with a different motivation. There are two major lines of study in this field: experimental and model-based investigations. The main focus of experimental studies includes early diagnosis of balance disorder, patient assessment, targeted lesion study, etc. On the other hand, model-based studies place an emphasis on comprehending the control law, which is responsible for preserving equilibrium. Keeping in view the theme of research, we will keep our focus on model-based studies. While reviewing model-based studies, a broad spectrum of models ranging from the simplest to the most complicated ones can be observed depending on the aims and objectives of the researcher [41]. Various important decisions must be taken regarding the modeling of the body and musculoskeletal dynamics, the complexity of sensory systems, some appropriate neural control techniques to use, and more precisely, to include nonlinearities and uncertainties in the model. The prior studies are reviewed in

this section to have a better knowledge of the strengths and shortcomings of the models available in the literature.

2.4 Posture movement

STS activity and the problems associated with it have traditionally been termed as a phenomenon linked purely with old age [44]. A person's ability to perform STS movements can be used to estimate their level of function. Being able to stand up from a sitting position is essential for a person's quality of life since it is associated with their level of functional independence. According to studies on the hierarchy of impairment, issues with STS begin later than problems with walking [42]. Since STS requires the body to work more against gravity than walking does, it is a physically demanding activity mechanically speaking. For this reason, the amount of STS research is very small as compared to work done on gait. Moreover, research on STS is done in recent times. Although it is fact that the problem in STS is very often an old age-related phenomenon; since for the ages above 48 years, muscles mass reduces rapidly almost 1-2.5

2.5 Biomechanical Model

Modeling human body motion, however, is not an easy task owing to the multifaceted nature of this. Indeed, this requires the understanding of internal/external biological and physical principles that govern human movement and coordination, as well as, keeping in mind the physical constraints of the overall system to provide the motion mechanism a realistic representation with high fidelity. Due to the highly complex nature of the human body and the forces from the environment that interact with it, despite over 30 years research of biomechanics. In this scenario, mathematical modelling provides another technique to analyze this problem. Given the dynamics of the system, its limitations, and the recovery actions permitted, some authors concentrated on predicting the set of states from which it is possible to recover a static equilibrium. In addition, the ankle strategy's limit was depicted in the instantaneous (CoM) position-velocity state space by pioneering biomechanics research [46,47]. This research was enhanced to integrate the hip method and a single or several steps of rehabilitation [48]. As a logical extension, this kind of modelling can be used to foretell the best rehabilitation plan [49-51]. Although, this strategy is completely depended on the system's dynamic features and current state. Both the perturbation and the control aspects of the balance are not specifically taken. The results of a given disturbance cannot be accurately predicted using such approaches, especially if the perturbation is time-varying and the reaction is not maximal.

2.6 Non-Linear Control system

Generally, linear mathematics is used to develop the biomechanical analysis of human movement. While these methods are effective in a variety of contexts but do not adequately capture the behaviour of the human body systems that are primarily nonlinear in nature [52]. Consequently, nonlinear analyses have gained popularity in the recent literature. Van Wouwe et al. [53] stabilized a nonlinear single link inverted pendulum model using an optimum linear controller, emphasizing the importance of nonlinear musculoskeletal dynamics, physiological noises, and feedback delays in movement. The theory of nonlinear control has been around for a little longer than its application to engineering problems. Khalil [54] and Zak [55] provided in detail the mathematical explanation and proofs of sliding mode control, optimal nonlinear control, backstepping, and vector field methods e.g., feedback linearization. These theories, on the other hand, are used and investigated for simple or classic nonlinear problems like the inverted pendulum model. Khalil [56] further studied the application of robust and nonlinear integrators to double inverted pendulum with switching through sliding mode control. So far, the main focus of research in biomechanical modeling has been nonlinear analysis of various motions e.g., for electrically simulated muscles, Hunt [57] employed nonlinear modeling and control. Reiner and Fuhr [58] discussed the use of functionally-electrical simulated (FES) muscles to assist paraplegic patients in standing up. They observed that nonlinear measures of variability, as opposed to linear measurements that reflect average variations around a mean state, are more useful for identifying dynamic stability. On a biped robot, Sadeghnejad et al. [62] researched the design and implementation of an inputoutput feedback linearization controller. This nonlinear control methodology has been shown to be more robust to state noise and to correct for changes in the ZMP (zero-moment-point) trajectory of a biped robot than previously applied optimal control methods. The results demonstrated that the proposed controller appears to be well-suited for use with real robots.

2.7 Posture Control Model

Human stance in an upright position is unstable in its normal state, even when there is no external disturbance. It is important to mention that numerous studies and many disagreements exist regarding how the CNS generates these corrective joints torques. This simplistic model omits the external disturbance. Motor commands stimulate and drive the musculotendon. The brain control system receives the sensory impulses that are related with the location and movement of the body from the sensory systems. The brain controller subsequently converts the sensory data received into motor instructions. The control theory focuses on how a controller may be set up in accordance with the sensory systems and plant characteristics to achieve the optimal behaviour of the plant to maintain postural stability.

Human posture in an upright stance is frequently modelled as an inverted pendulum with a single joint that rotates at the ankle joint and only moves in the sagittal plane [32, 34]. The smooth and tendon muscles in the lower legs are primarily responsible for controlling muscular activity during upright posture, according to empirical data, which supports the single joint approach [64]. By stating that the motor function is simply transferred into the ankle torque, one not only simplifies body mechanics but also trivializes the characteristics of muscles and tendons. The simplified and linearized plant model with assumed simplification defined by [64] is given below:

$$I\ddot{\theta} = mgk\dot{\theta}(t) + u(t) + n(t)w(t)$$

where I is the body's moment of inertia, $\ddot{\theta}$ is the angular acceleration and θ is the angular deviation of body from upright position, m is the mass, k is the distance of COM of body to the ankle joint, g is the acceleration due to gravity, and $u(t)$ represents the torque actuation at the ankle joint specified by the neural controller forward command signal. $w(t)$ is the white Gaussian noise and $n(t)$ represents the noise level.

2.8 Artificial Intelligence

Since the creation of the computer, we have constantly daydreamed about building artificial intelligence that is, a system that can think for itself. The capacity to learn and grow as a result of experience is one of the most important characteristics of intelligent behaviour. Although we have the ability to accomplish this since birth, we still do not fully understand how learning actually works. The creation of methods and systems that enable computers to learn the underlying structure of a data collection is the focus of the field of machine learning. In the programme created by a person, this is done with the intention of solving a problem without the need of explicit descriptions. Artificial intelligence is the simulation of human cognitive processes by technology, particularly computer systems (AI). Examples of particular AI applications include expert systems, machine learning, natural language processing, speech recognition, and machine vision. AI systems typically consume a huge amount of labelled training data, analyse it for correlations and patterns, and then use these patterns to predict future states. AI is important because, in some situations, it can execute tasks better than people can and because it may give businesses previously unattainable insights into their processes. Additional subcategories of AI include machine learning and deep learning, as seen in figure 2.1.

2.8.1 Machine Learning

Machine learning is a subset of AI which enables computers to learn without being explicitly taught. Machine learning was created because of pattern recognition and the

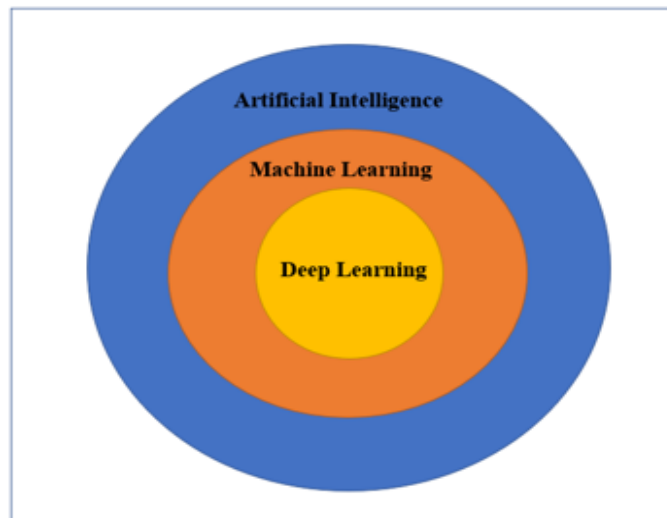


Figure 2.1: Types of AI

notion that computers could learn without being programmed to perform certain tasks (ML). Researchers studying artificial intelligence wanted to determine if computers could learn from data. They gain knowledge from past calculations to deliver reliable, replicable judgements and outcomes. Some of the technique used in supervised machine learning are given below,

- Random forest regression
- Support vector regression
- Decision tree regression

2.8.2 Deep Learning

Deep learning is a subset of machine learning. A form of artificial neural network-based machine learning in which input is processed through numerous layers to gradually extract higher-level features.

2.8.2.1 Artificial Neural Networks (ANN)

The perceptron, an algorithm modelled after the biological neuron, is the fundamental unit of an ANN. A human neuron uses dendrites to gather input from other neurons and adds up all the inputs. A result is generated if the sum exceeds a predetermined limit.

The perceptron is a mathematical representation of a neuron, as seen in Figure 2.3. It receives weighted inputs, which are combined, sent to an activation function, and then it receives outputs. The activation function determines whether an output should be generated.

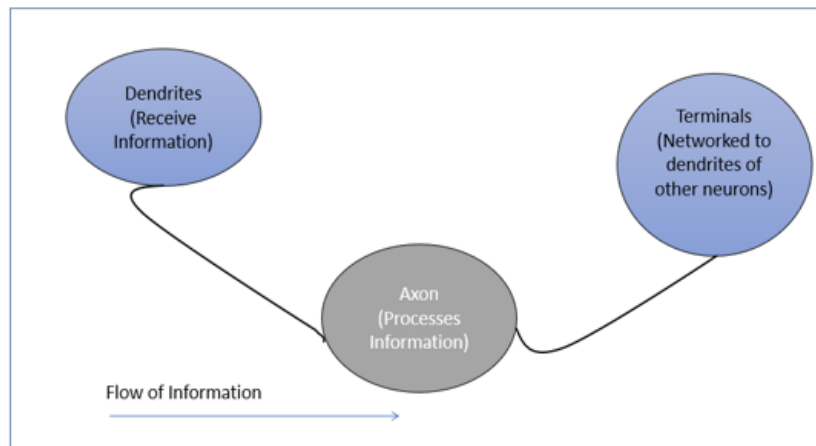


Figure 2.2: Perceptron

Weights are changed to reduce output error when training a perceptron. The difference between the desired and the actual output is referred to as output error as shown in figure 2.4.

2.9 Types of Learning

There are numerous ways to classify learning algorithms, the accepted practice in the machine learning community is to categorize them according to the types of data sets they employ. Unsupervised learning, reinforcement learning, and supervised learning are the three main classes that are used and explain below.

2.9.1 Supervised Learning

In supervised learning, each example has an associated output in addition to the input from our data collection. When a model is trained using supervised learning, it seeks to deduce the underlying principles that explain how the inputs relate to the corresponding outputs. Regression and classification are the two most typical supervised learning-related machine

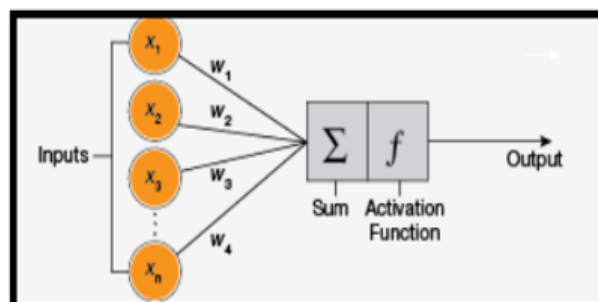


Figure 2.3: Representation of a neuron

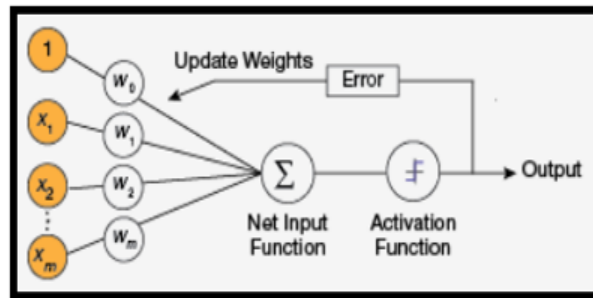


Figure 2.4: Actual output with desired output

learning issues. The distinction between these problems, which are both of a similar kind, is the kind of outputs connected to each case.

2.9.2 Unsupervised Learning

Unsupervised learning in which no labeling of data. The learning algorithm in this situation has no specific objective to work against. This may arise in a variety of circumstances when there is either no clear solution or we are just unaware of it beforehand. As a result, unsupervised learning is frequently employed to classify samples [69]. It should be noted that this is a hyper-parameter because the learning algorithm cannot decide how many groups to divide the data into on its own.

2.9.3 Reinforcement Learning

The way reinforcement learning operates differs significantly from the other two types. It draws its inspiration from behavioral psychology, particularly the "carrot and stick" method. We force the machine learning algorithm to interact with a dynamic environment where it must complete a task to achieve a certain goal [70] rather than feeding it data. It's possible that the model was not even instructed on how or what to do to accomplish this. Instead, after the model has completed an action, it is reinforced negatively or positively. The model will next need to learn what actions to take and how to execute them to maximize positive outcomes while minimizing adverse ones [71].

2.10 Data Collection

One of the most parts during AI implementation is data collection. Because data collection gives information about the inputs and outputs of the system or any model. If output of data is required in form of continuous form, then regression required. Similarly, if required output is in discrete form then classification required. Although, if inputs and outputs are defined or known then supervised learning is implemented otherwise unsupervised

learning. The quantity and caliber of data used as input is one of the key determinants of how well a trained model performs. One may even assert that the quality of the data used to train the machine learning model determines how effective it is. As a result, it's critical to consider the type of data required for the activity at hand as well as an effective method of gathering it [72]. When training a model, simply collecting a lot of data, and applying it in its unprocessed form might not produce the best results.

2.10.1 Structuring the Data

It is crucial that we divide the data into two sets before applying any alterations to the raw data. One will be designated as the training set, which will be used to develop our model, and the other will be designated as the test set, which will be used to gauge how well the trained model performs.

2.10.2 Data Processing

When using machine learning algorithms, the data used as input to the learning algorithm may require some sort of preparation, either to increase performance or expedite model fitting, for a variety of reasons. The features in the data frequently have different scales and, in some circumstances, discrepancies on multiple magnitudes.

Chapter 3

Experimental data validation & analysis through machine learning approaches

The Biomechanics lab of Riphah International University is used to collect experimental data for posture motion. The goal is to create a model that closely resembles the movement patterns of real people. We used reflective markers, an optical motion capture system with several infrared cameras, a 4-beam-2-axes force platform, and healthy participants to collect data to simulate posture motion.

3.1 Experiment Apparatus

During the experiment following apparatus and software are required,

- Pasco force plates
- Infra-red cameras
- Calibration square
- Optihub
- PASCO 850 universal interface
- Software used for motion and force capture are Optitrack Motive, Capstone and MATLAB (MoCap Toolbox) for data analysis.

3.2 Subjects for Experiment

Six healthy participants, aged 22 ± 2 years, weighing 70.5 ± 2.5 kg, and standing 1.70 m tall, gave their informed and previous agreement to take part in the study. These participants

were chosen from young people with no prior history of STS motion problem. Six healthy volunteers' STS motion was captured using a motion-capture system based on 4-Flex-3 infrared cameras and 13 markers." The information was utilized to create force and motion profiles.

3.3 Equipment and Calibration

There are no specific guidelines in the literature that can be used to help us decide on the ideal number and proper location of cameras, markers, and cameras for reliable motion capture. A calibration wand is required for camera calibration, and a calibration square is required for establishing the frame of reference in the motion capture space. Since cameras are sensitive to changes in temperature, light, and position, recalibration is usually required to make sure. Before each trial, the force plate was verified to make sure there was no error. The Motive Edit environment was used to manually number each marker after motion data had been gathered. These markers were first individually numbered, and then they were grouped together and given segment names. In Motive edit mode, the segment labels were also manually assigned for each trial. Motion capture data is exported by Motive in two different file formats: a motion capture-specific *.tak* format and a general *.c3d* format.

3.4 Challenges during Experiment

Initially, some mock experimentation was done to devise a set of protocols regarding appropriate positioning of equipment, sampling frequency for data acquisition, number, and position of markers on a subject's body and so on. Infra-red cameras are very sensitive to changes in ambient light and slight disturbance in their positioning. Due to unavailability of skin-tight motion capturing suit and Velcro bands, we faced additional difficulty in making all markers visible to cameras throughout the trials. Moreover, infra-red cameras may pick reflection from a shiny surface like doorknobs or zippers on garments. Each such item was identified and was covered with masking tape. The mock experimentation continued for some 1 week.

3.4.1 Set of Protocols

Eventually, a set of protocols was finalized to conduct the actual experiments which are:

- On the left side of each segment 13 markers are attached.
- 3 markers on shank.
- 3 markers on thigh.

- 3 markers on foot.
- 3 markers on trunk.
- By using hairband 1 marker is attached with head.
- Healthy subjects participate in experiment
- Appropriate positioning of equipment
- Sampling frequency for data acquisition
- Number and position of markers on a subject's body
- During these trials the subject was selected in a chair, arms crossed across the chest so that head, arm, and trunk could be treated as a one segment. If arms are kept hanging during motion, their movement may add error to the posture dynamics for a model that incorporates both hands into a consolidated segment called head arm trunk.
- The two feet should keep close so that both ankles should rotate about same axis. To start the trail, the subject was asked to stand up at normal speed and then sit down after 3-4seconds.

3.5 Motion Capture

Four infra red OptiTrack cameras are used to capture the motion at 100Hz. Using OptiTrack Motive data acquisition software to generate different files. Figure 3.1 shows how data is converted into .C3d and .CSV format.

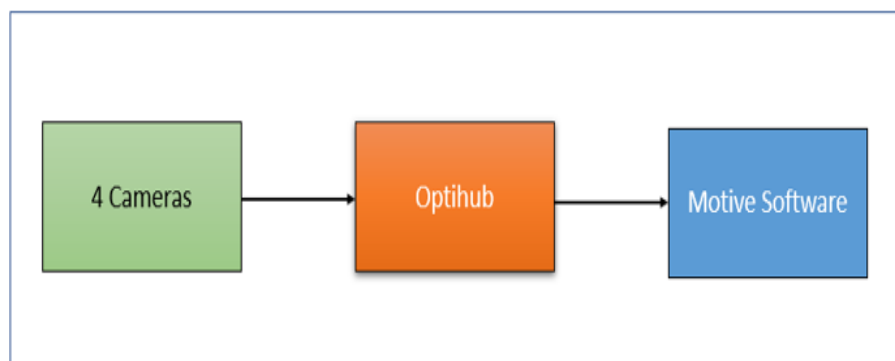


Figure 3.1: Motion capture workflow

3.6 Infra-Red Cameras

Infra-Red OptiTrack Cameras are used in this research for motion capture. Figure 3.2 shows the OptiTrack camera. OptiTrack cameras are sensitive to following:

- Very Sensitive to change in position or any disturbance.
- Unavailability of skin-tight motion-capturing suit and Velcro band.
- Pick reflection from a shiny surface like doorknobs or zippers on garments.

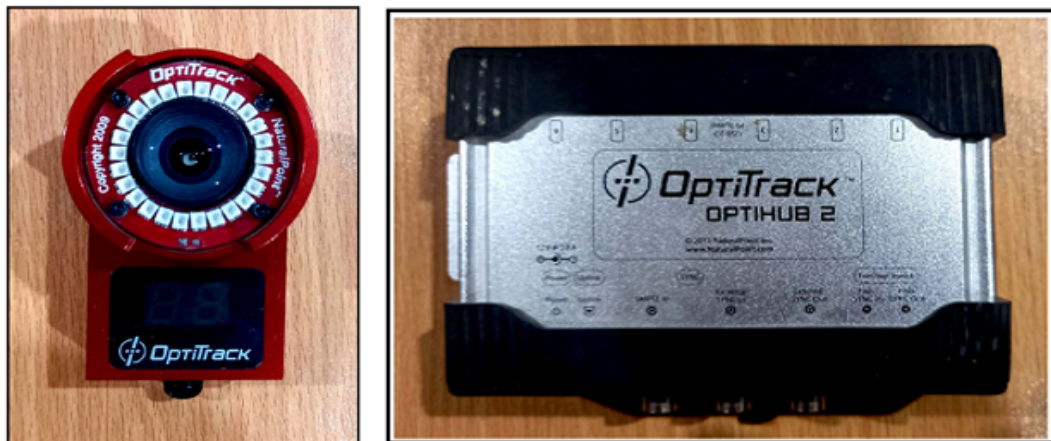


Figure 3.2: Infra-Red Optitrack Camera and Optihub

3.7 Data Acquisition and Motive Screen

In LIVE mode, on the upper part of the screen 3D motion of marker is shown and cameras are also shown on their respective positions. In lower part, separate 2D images (marker movements) from individual cameras can be seen. Figure 3.3 shows the complete setup of motion capture. Movement is recorded and video is played back in Motive platform to check if all markers were visible throughout the clip. Motive environment interface along with four cameras is shown in figure 3.4. In edit mode, each marker is assigned a number and a group of markers is labeled as segments, ‘ankle,’ knee, and hip’ joint along with head position.’’The data file is exported in CSV and C3D formats to be analyzed in the MoCap environment.

3.8 Force Capture

Force data too were collected using the Pasco force plate at 100Hz, using Capstone software. Figure 3.4 show that data generated by Pasco force plate is converted into .CSV format. Figure 3.3 shows the force plate which will give data of subject movements.

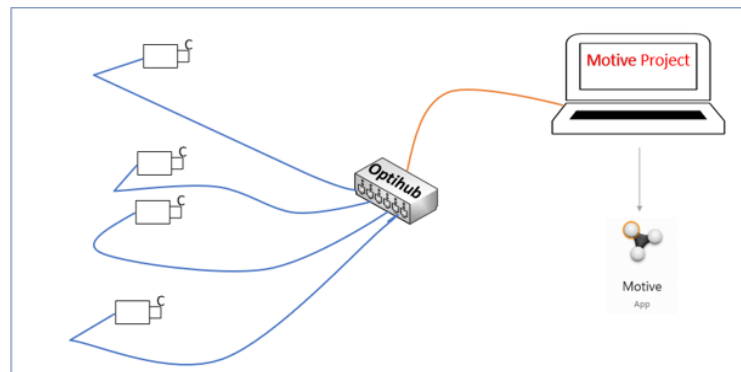


Figure 3.3: Experimental setup

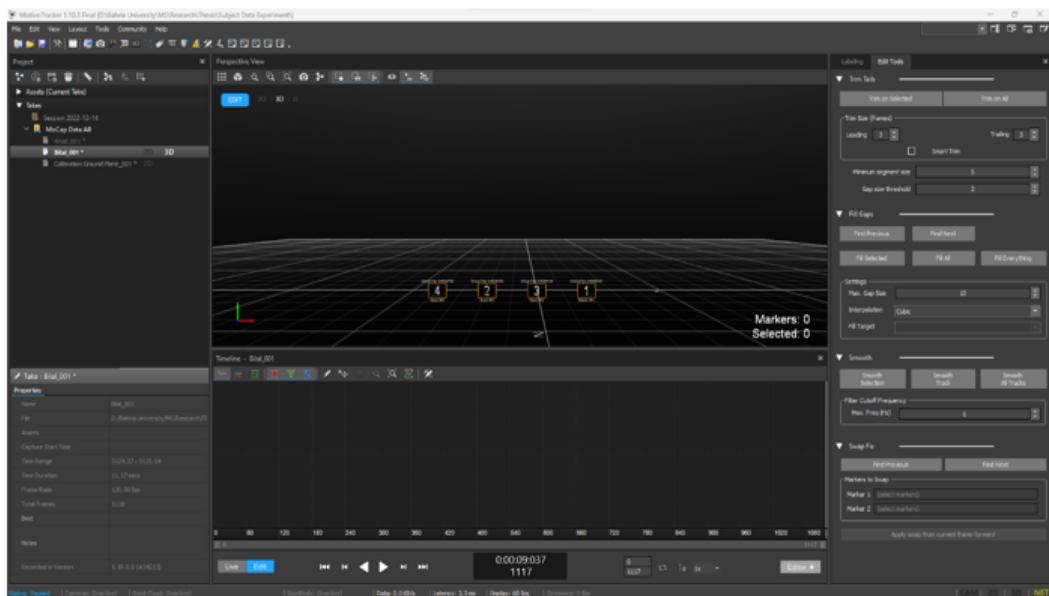


Figure 3.4: Optitrack Motive software Interface

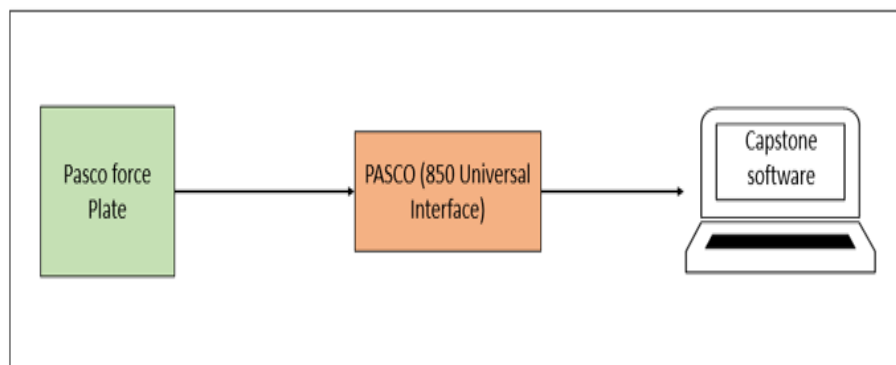


Figure 3.5: Experimental setup for force capture

Firstly, Pasco force plate is connected to Pasco 850 universal interface. Pasco 850 universal interface linked Pasco force plate with the Capstone software although, figure

3.6 show Pasco 850 universal interface. Capstone software shows the real time data also we can import the data in different formats i.e .csv

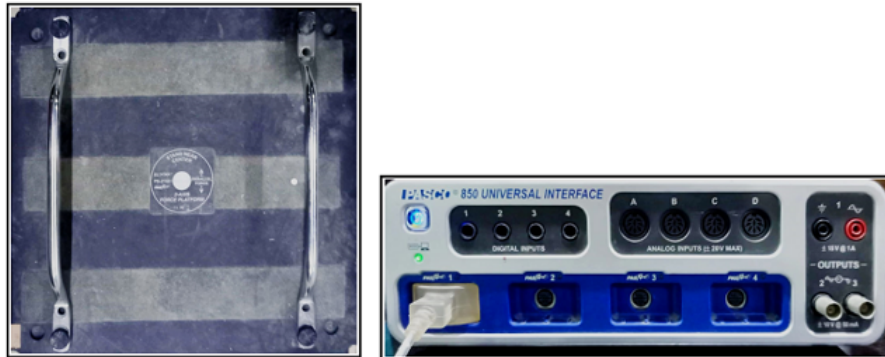


Figure 3.6: Pasco force plate and 850 universal interface

3.9 Mocap Toolbox

The MoCap toolbox is a free MATLAB toolbox that includes features for motion capture data analysis and display. Our motion data was recorded in the universal *.c3d* file format, which is supported by it. The toolbox must be added to the MATLAB path variable before use.

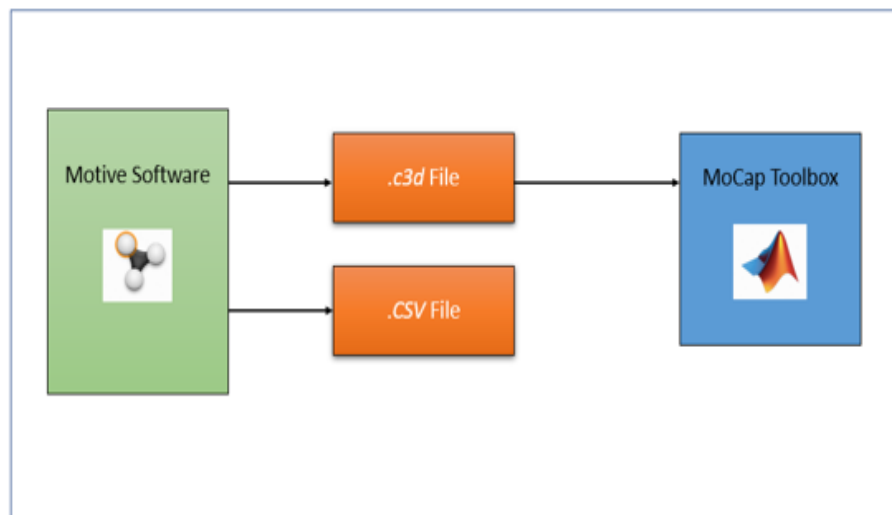


Figure 3.7: Data acquisition and data analysis

3.9.1 Reading and plotting the MoCap Data

Given that the motion capture data is available in the file, for example, Bilal_003.c3d. Below figure shows the MATLAB code which would generate animation, plots of marker

as white dot. Moreover, change of color, marker size and orientation. Figure 3.8 and 3.9 shows the animation in marker space and give analysis in joint space.

```

Editor - C:\Users\engr\OneDrive\Desktop\Mocap.m
Mocap.m x +
1 - X=mcread('Bilal_003.c3d'); %Store data in Variable X
2 - Y=mcinitanimpar; %Initialize animation in marker space
3 - mcplotframe(X,100) %Plot 100 frames
4
5

```

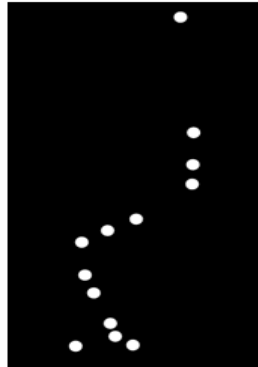


Figure 3.8: Animation in marker space

```

8 - Y.colors='wkkkk'; %Marker color black or white
9 - Y.msize=5; %Marker size
10
11 - Y.conn=[1 2; 2 3; 3 1; 6 5; 5 4; 9 8; 8 7; 12 11; 11 10]; %Join markers
12
13 - mcplotframe(X,100,Y) %Plot 100 frame with markers connected
14

```

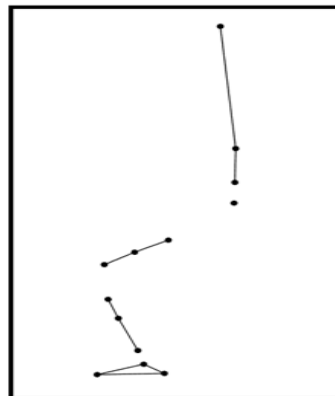


Figure 3.9: Join Markers

3.9.2 Motion Data Analysis

MoCap uses linear interpolation to recover missing markers. Using MoCap, markers can be assigned with numbers, so can be segments given names. Motion Capture and data

validation is shown in figure 3.10. All the motion data are used to reconstruct the motion of every subject and for every trail. The reconstructed animation is used to determine/the motion. To normalize motion time by different subjects and during multiple trails.

```

15
16-   Y.fps=15;           %Frame per second rate
17
18-   Y.conn=[1 2;2 3;3 1;1 9;9 12;12 10]; %Connect markers
19
20-   stsMot=mcanimate(X,Y); %Motion Animation
21

```

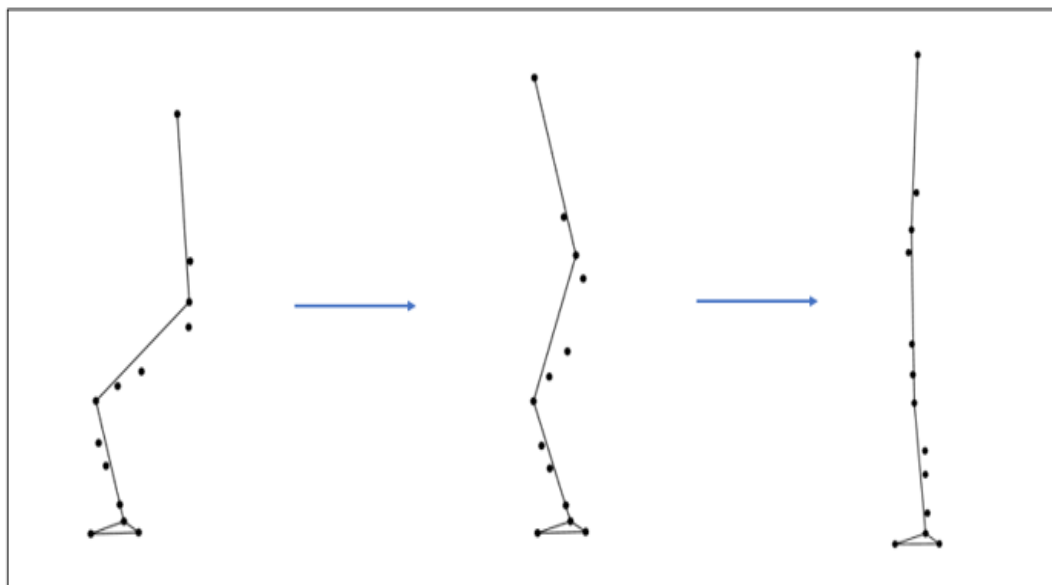


Figure 3.10: Motion Capture and data validation

3.10 Machine Learning Approach

This research focus on traditional machine learning approach used to improve robotic and exoskeleton design. Input parameters are defined and implement feature extraction on I/P parameters, then a regression model is designed to predicts output. By using head positions of different experimental objects, regression model will predict the positions of ankle, knee, and hip joints. Therefore, on head positions defined as input and position of joints are outputs of the model. Figure shows workflow of neural network along with plant.

AI approach contributes to a better knowledge of the postural control and STS mechanism. In this research supervised learning is used because inputs and outputs are defined or known. So, the techniques used under supervised learning are:

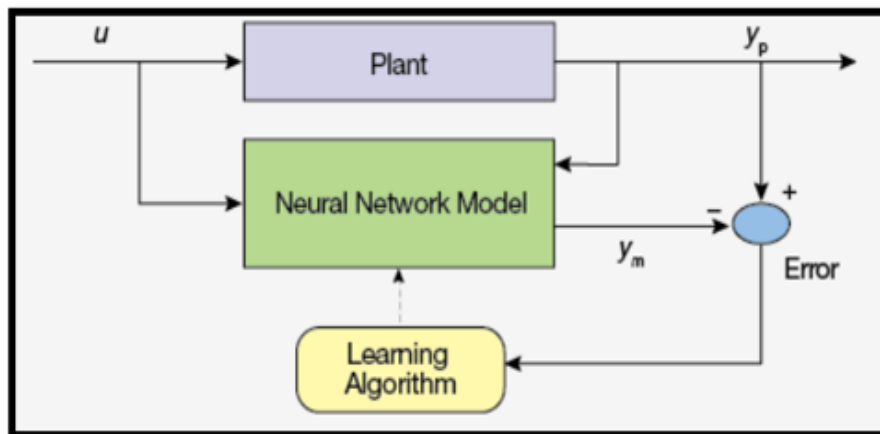


Figure 3.11: Neural Network Model

- Support vector regression
- Random forest regression
- Decision tree regression

3.10.1 Support Vector Regression

Support Vector Machines (SVM) are a form of a supervised machine learning technique that offers data analysis for regression and classification. SVM is mostly used for classification, though they can also be used for regression. Find the hyperplane that connects the dependent and independent variables in a linear fashion. A collection of mathematical operations known as the kernel are used by SVM algorithms. The SVM's kernel oversees formatting the input data according to the specifications. SVM uses a variety of RBF and Polynomial function are used to create a non-linear hyperplane.

3.10.1.1 PYTHON Implementation

Following steps will be followed to implement space vector regression on research problem in SPYDER (PYTHON 3.9). Moreover, figure 3.12 shows the interface of SPYDER in which space vector regression is implemented.

- Implementation
- Importing the libraries and dataset
- Feature scaling (Since in SVR we have an implicit relationship equation between independent and dependent variables, so we need to apply feature scaling. For SLR, MLR and polynomial regression we have an explicit relationship and we do not use feature scaling.)

- Training the SVR dataset on the whole dataset.
- Predicting a new result.
- Visualizing the SVR results.
- Visualizing the SVR results for higher resolution and smoother curve.

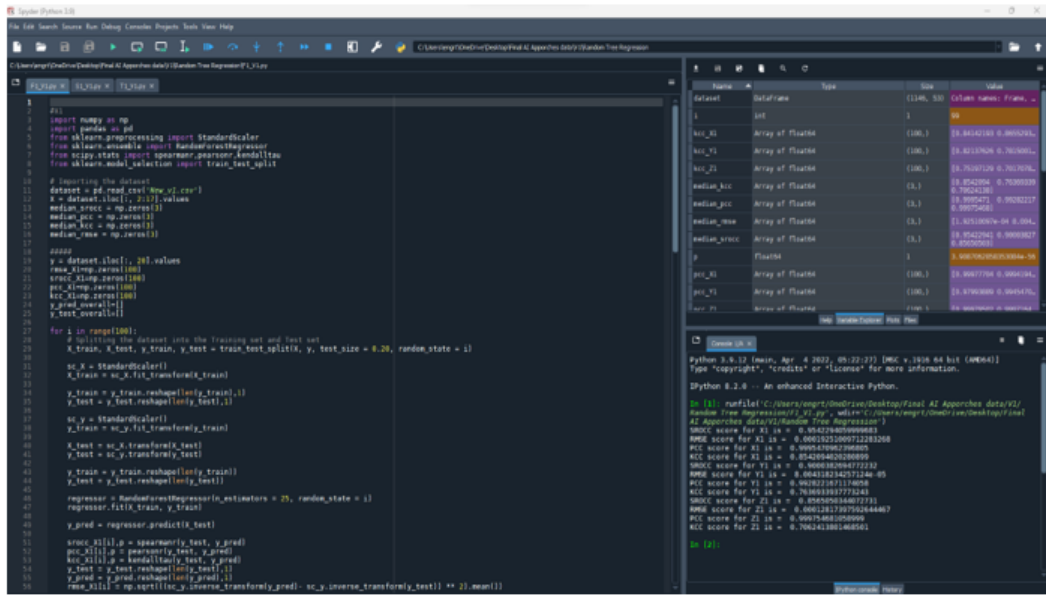


Figure 3.12: Python interface using Support Vector Regression

3.10.1.2 Results

Implement space vector regression technique of machine learning by using SPYDER platform improve previous design [80]. By using head positions of different experimental objects, regression model will predict the positions of ankle, knee, and hip joints. Therefore, on head positions defined as input and position of joints are outputs of the model. Figure 3.13-15 shows the predicted position values of Ankle, knee and hip joint trained upon head position.

3.10.2 Decision Tree Regression

The predictor space is stratified or segmented into a number of straightforward sections in tree-based approaches for regression and classification. Decision tree methods are a subset of machine learning techniques that segment the predictor space using a set of splitting rules that can be encapsulated in a tree. These techniques’ central tenet is to divide the universe into sections and pick out a few representative centroids.

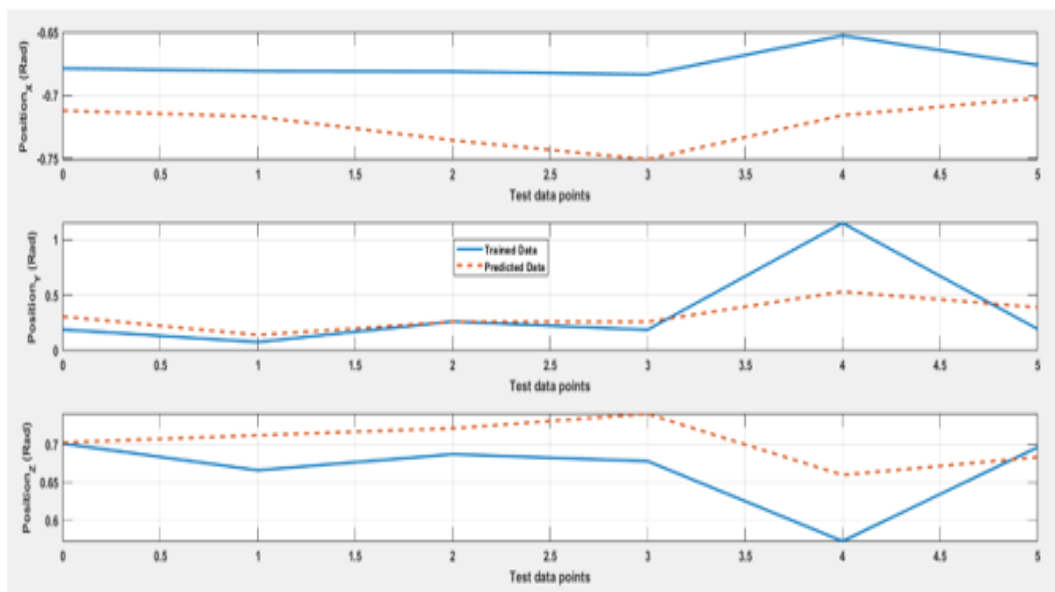


Figure 3.13: Trained and predicted data set of Ankle joint

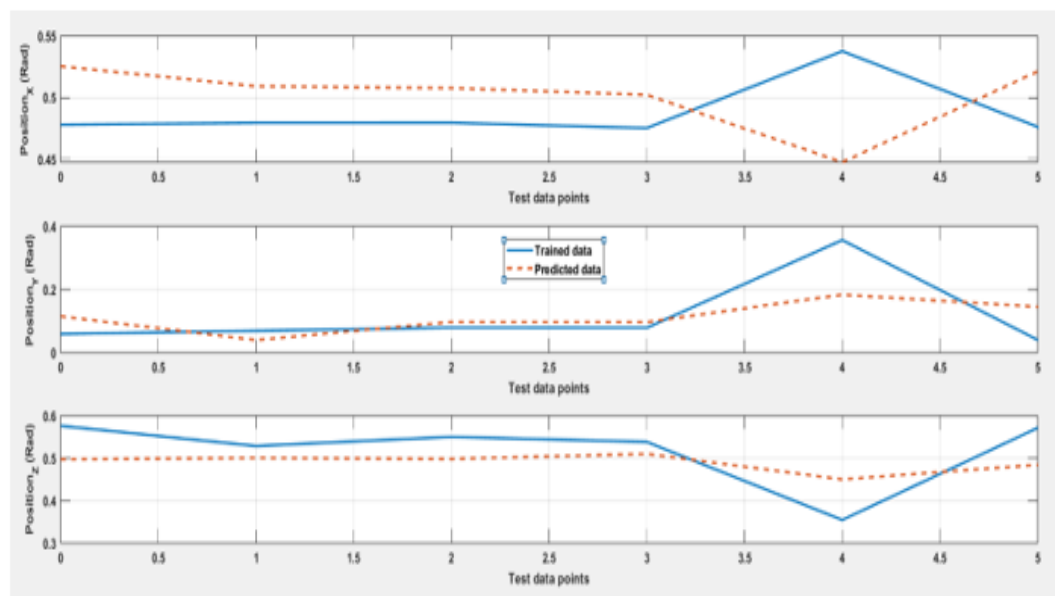


Figure 3.14: Trained and predicted data set of Knee joint

3.10.2.1 PYTHON Implementation

Following steps will be followed to implement decision tree regression on research problem in SPYDER (PYTHON 3.9). Moreover, figure 3.16 shows the interface of SPYDER in which decision tree regression is implemented.

- Importing the libraries.
- Importing the dataset.

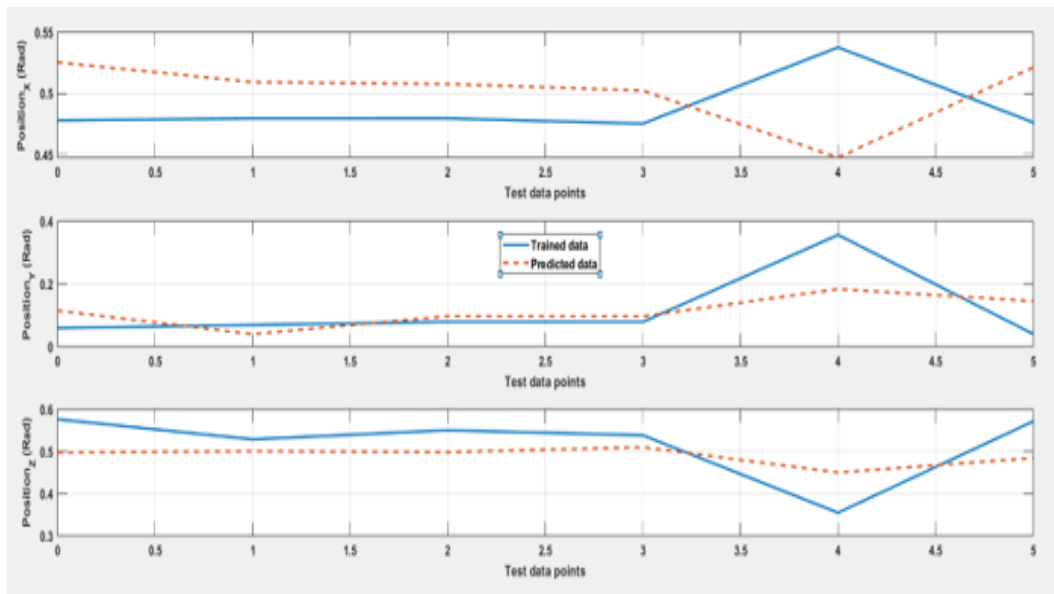


Figure 3.15: Trained and predicted data set of Hip joint

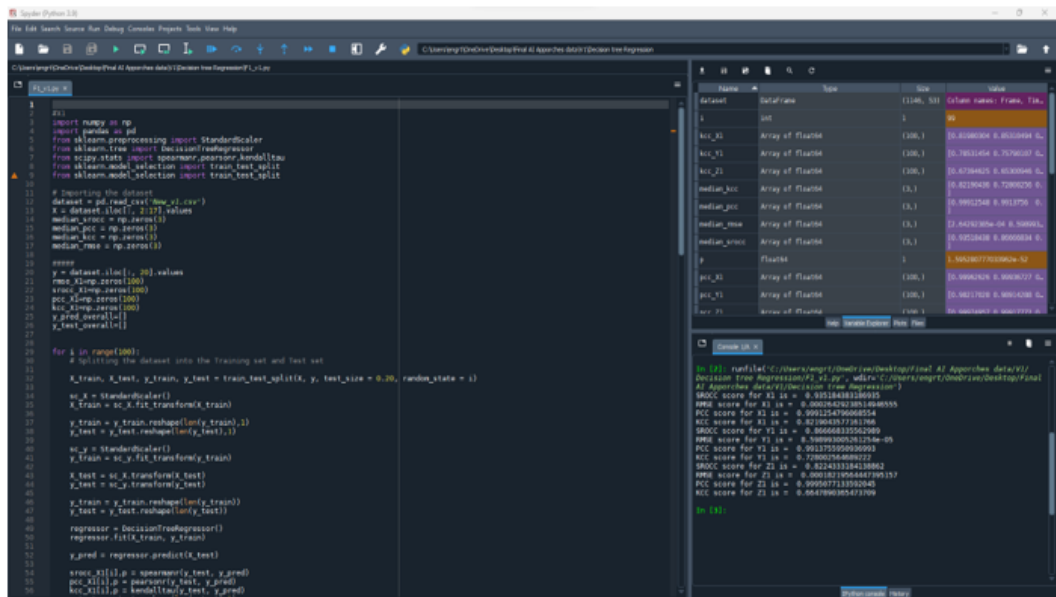


Figure 3.16: Python interface using Decision Tree Regression

- Training the decision tree algorithm.
- Predicting new values.
- Visualizing the decision tree regression results.
- Evaluating the model.
- We are using the same dataset of employee positions and salary.

- The problem is same that we need to predict the salary of the perspective new employee.
- The decision tree regression algorithm is not very well adapted to these simple datasets.
- It is usually useful for datasets involving multiple independent variables.
- We do not need to apply feature scaling for the decision tree algorithm.

3.10.2.2 Results

By using head positions of different experimental objects, regression model will predict the positions of ankle, knee, and hip joints. Implement Decision tree regression technique of machine learning by using SPYDER platform to improve previous design [80] and for analysis with above proposed technique. Therefore, on head positions defined as input and position of joints are outputs of the model. Figure 3.17-19 shows the predicted position values of Ankle, knee and hip joint trained upon head position.

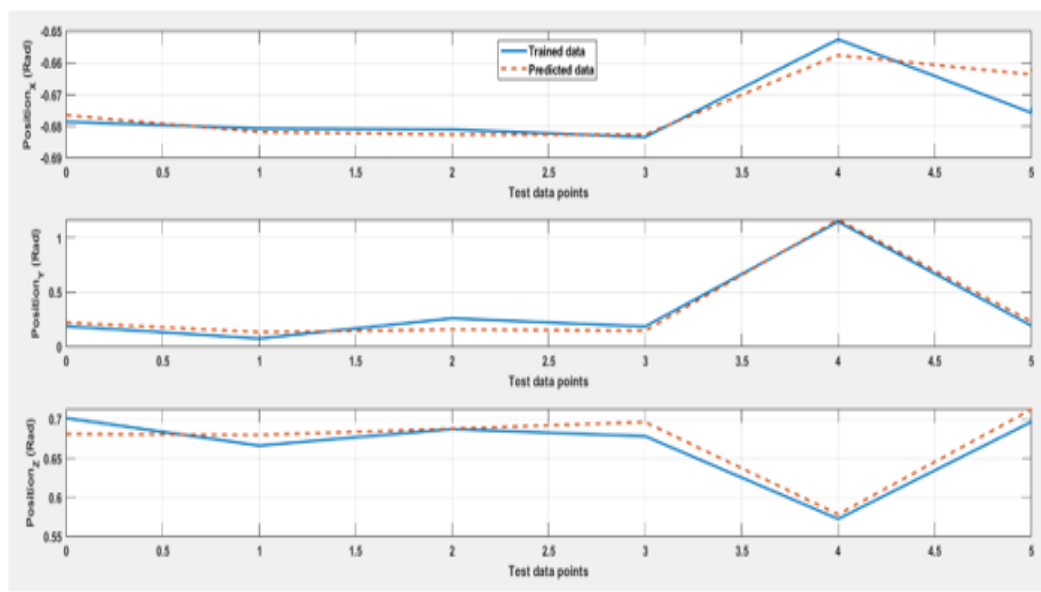


Figure 3.17: Trained and predicted data set of Ankle joint

3.10.3 Random Forest Regression

To address classification and regression problems, the Random Forest Algorithm, a very well-liked supervised machine learning method, is used. A forest is made up of numerous different species of trees, and the forest will be more vigorous the more trees there are. Decision tree classification and random forest have many similarities. A form of ensemble

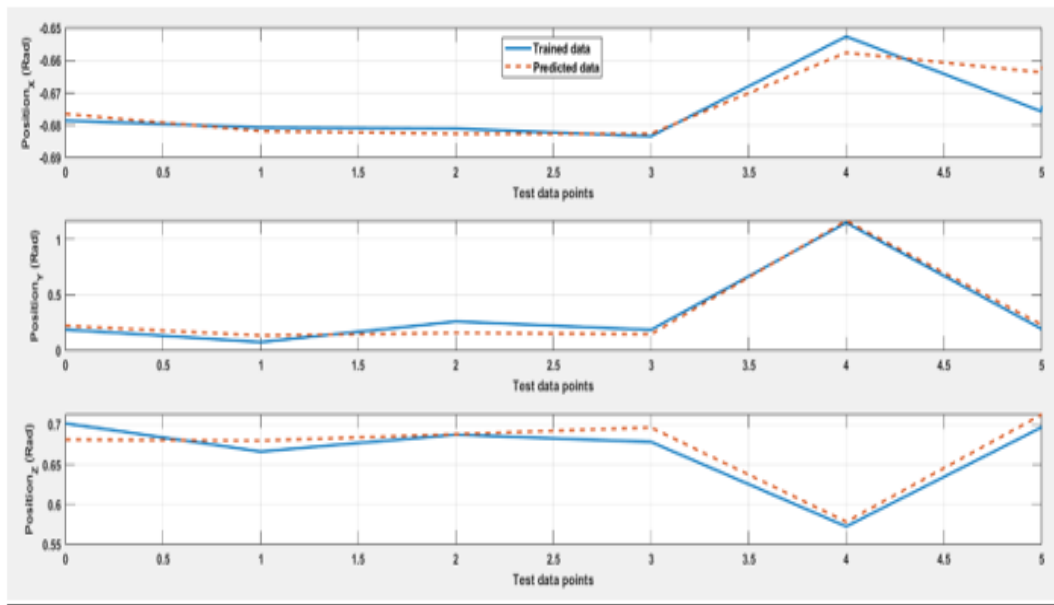


Figure 3.18: Trained and predicted data set of Knee joint

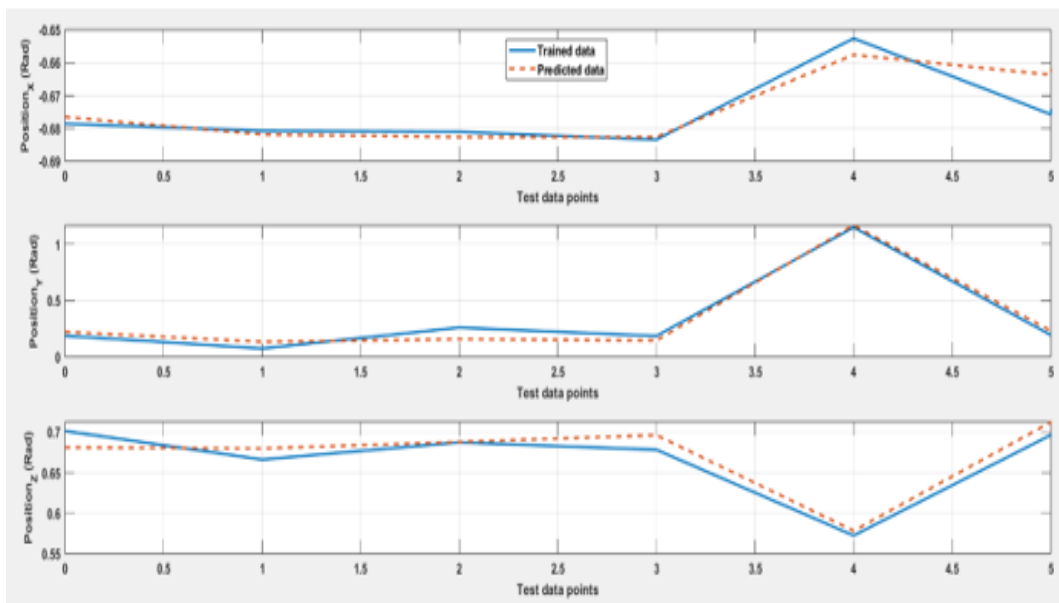


Figure 3.19: Trained and predicted data set of Hip joint

learning is random forest. In ensemble learning, you can combine several of the same algorithms or distinct algorithms to create a more effective method. In this way, as the number of trees in a Random Forest Algorithm increase, so do its accuracy and ability to solve problems.

3.10.3.1 PYTHON Implementation

Following steps will be followed to implement random forest regression on research problem in SPYDER (PYTHON 3.9). Moreover, figure 4.20 shows the interface of SPYDER in which random forest regression is implemented.

- Since, it is similar to decision tree regression.
- We will use most of the code from the last lecture i.e., decision tree regression.
- Only the training model part of the code will be changed. Rest of the code will be the same as the decision tree regression.

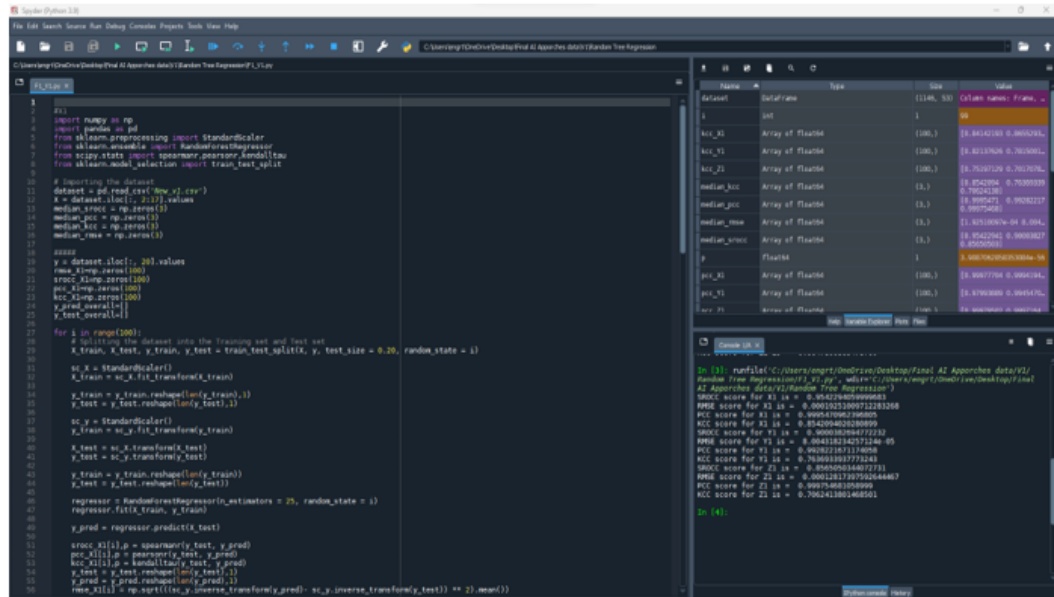


Figure 3.20: Python interface using Random Forest Regression

3.10.3.2 Results

By using head positions of different experimental objects, regression model will predict the positions of ankle, knee, and hip joints. Implement Decision tree regression technique of machine learning by using SPYDER platform to improve previous design [80] and for analysis with above proposed technique. Therefore, on head positions defined as input and position of joints are outputs of the model. Figure 3.17-19 shows the predicted position values of Ankle, knee and hip joint trained upon head position.

RMSE value gives the error of original value and the predicted value. So in graphs its clearly shown that the Random forest regression technique give much more accurate results than the pervious technique ANFIS and also better than SVM, and Decision tree regression. Also the Figure 3.24 shows the average RMSE of all techniques.

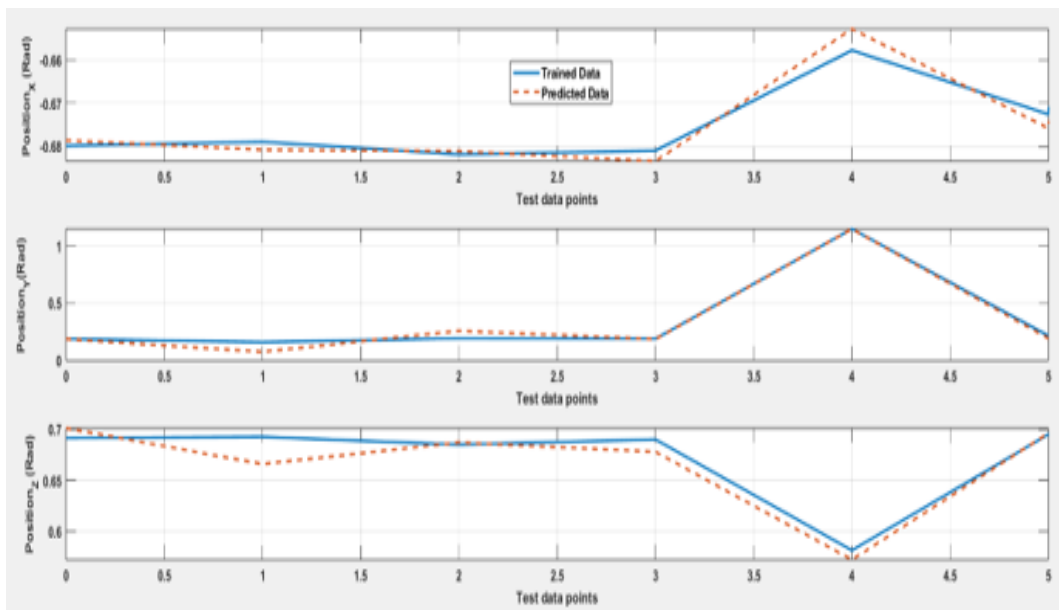


Figure 3.21: Trained and predicted data set of Ankle joint

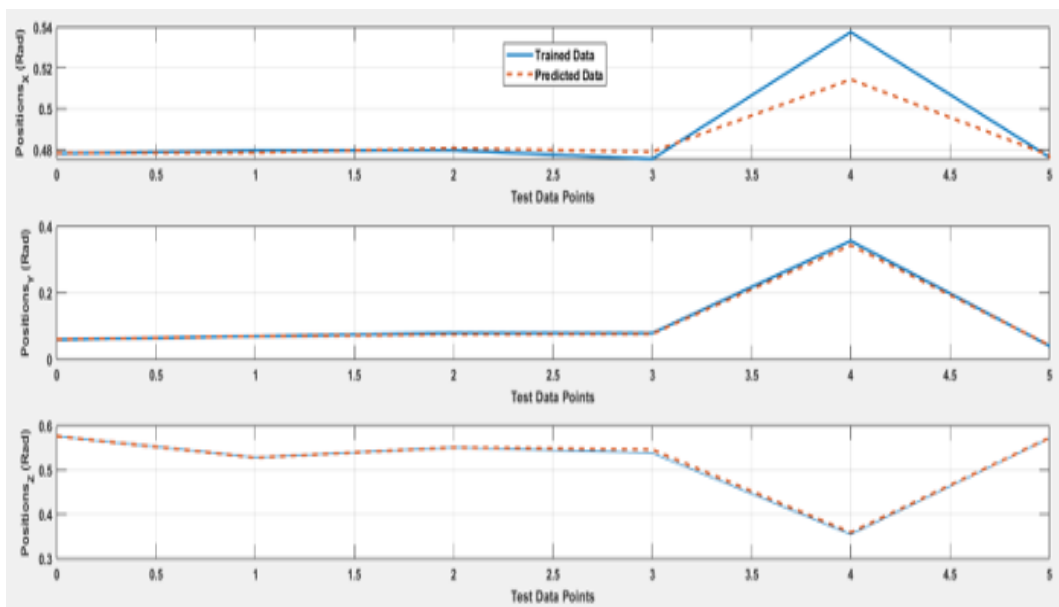


Figure 3.22: Trained and predicted data set of Knee joint

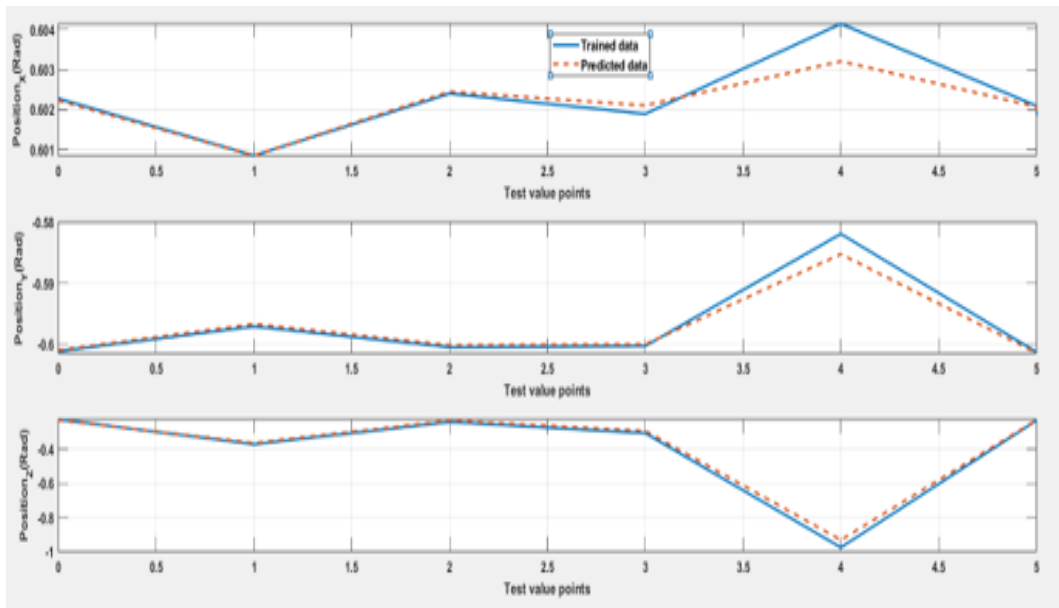


Figure 3.23: Trained and predicted data set of Hip joint

ANFIS [75]	RMSE
Ankle	0.0628
Knee	0.0663
Hip	0.0299

SV	RMSE
Ankle	0.00356548
Knee	0.00996816
Hip	0.005818833

DT	RMSE
Ankle	0.000175104
Knee	0.000642754
Hip	0.0001155214

RF	RMSE
Ankle	0.0000133576
Knee	0.0000560149
Hip	0.0000630295

Figure 3.24: Comparison of previous and applied techniques

Chapter 4

Postural Stability of a Single Link Model

In this chapter, we examine a nonlinear control application to a postural stability-related single link biomechanical model. As a result, a sophisticated biomechanical nonlinear mathematical model of the musculoskeletal system generates suitable movement strategies to carry out the plan. One of the key issues in control theory and applications is output feedback control for uncertain nonlinear systems. In order to maintain postural balance and sit-to-stand (STS) movement, feedback linearization mimics the control activity of the central nervous system (CNS).

4.1 Non-Linear Biomechanical model

The stabilising movements are created around the ankle joint for minor disturbances. Human body mechanics during posture movement are described as a two segment structure with torque actuation at the ankle joint, keeping in mind the stabilisation difficulty for tiny perturbations. A single section is used to represent the head, arms, trunk, thighs, and legs over the still feet. The ankle joint can be rotated via this section. In the anterior-posterior directions, the foot length corresponds to the BOS. In the sagittal plane shown in figure 4.1.

Mass of the segment is denoted by m , segment length is denoted by l , moment of inertia is denoted by I . Distance from the joint to COM is represented by k , where θ is angle of ankle joint and input is torque τ . Nonlinear biomechanical model is written in mathematical form is given below,

$$\ddot{\theta} = \frac{\tau + mgk \sin \theta}{I + mk^2} \quad (4.1)$$

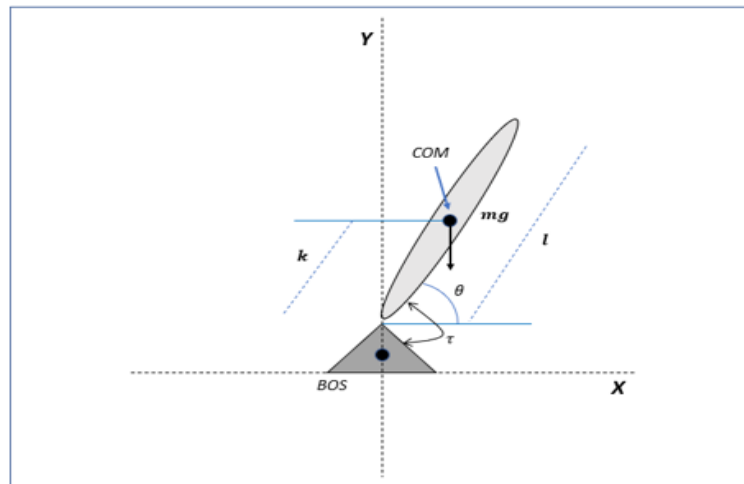


Figure 4.1: Segment Model

Parameters	Symbol	Values
Inertia of body	i	$2.633 \text{ Nm}^2/\text{kg}^2$
Body segment length	l	1.56m
Distance from COM to joint	k	0.98m
Acceleration due to gravity	g	$9.8\text{m}/\text{s}^2$
Mass of body	m	75.5kg

Figure 4.2: Parameters with values

Let suppose,

$$\theta = x_1$$

$$\dot{\theta} = \dot{x}_1 = x_2$$

$$\ddot{\theta} = \ddot{x}_1 = \dot{x}_2$$

By using above assumptions,

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= \frac{\tau + mgk \sin x_1}{I + mk^2} \end{aligned} \quad (4.2)$$

As we know that state equation,

$$\dot{x}(t) = Ax(t) + Bu(t)$$

$$\dot{y}(t) = Cx(t) + Du(t)$$

Now the state equation of proposed model is,

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} x_2 \\ \frac{mgk \sin x_1}{I+mk^2} \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{\tau}{I+mk^2} \end{bmatrix} \quad (4.3)$$

$$y = \begin{bmatrix} 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

By using the figure 4.2 below Eq 4.2 becomes,

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} x_2 \\ 11.8829 \end{bmatrix} + \begin{bmatrix} 0 \\ 0.0205 \end{bmatrix}$$

$$y = \begin{bmatrix} 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

4.2 Extended High Gain Observer Design

Modeling of CNS will be represented by an extended high gain observer (EHGO) which is based on a feedback linearization controller. Basically, EHGO works as a disturbance estimator and a soft sensor of the internal dynamics, respectively. Psychological structures delays and noises cannot be controlled in the postural control system therefore feedback linearization control is used. Feedback linearization generates torques at joints for postural recovery and EHGO will estimate delays. Moreover, a disturbance estimator can be used to achieve feedback linearization in the presence of uncertainties. But x and σ are not measured as the only measured signal is y . To design an observer that estimates x and σ , we extend the dynamics of the system by treating σ as an additional state. The function ϕ is unknown but due to the robustness of high-gain observers, we can build a third order observer to estimate x and σ . The extended system is given by,

$$\dot{x}_1 = x_2$$

$$\dot{x}_2 = \sigma + u$$

$$\dot{\phi} = \varphi(t, x, u)$$

$$y = x_1$$

As we know that,

$$\sigma = \phi(t, x)$$

So, by using Eq 4.2,

$$\begin{aligned}\sigma &= \phi(t, x) = \frac{\tau + mgk \sin x_1}{I + mk^2} \\ \dot{\sigma} &= \varphi(t, x, u) \\ \varphi(t, x, u) &= \frac{\rho \phi}{\delta t} + \frac{\rho \phi}{\delta x_1} x_2 + \frac{\rho \phi}{\delta x_2} [\phi(t, x) + u] + \dots\end{aligned}\quad (4.4)$$

By using Eq 4.4,

$$\dot{\sigma} = \varphi = \left(\frac{mgk \cos x_1}{I + mk^2} \right) x_2$$

Redefining the state variables,

$$\begin{aligned}x_1 &= x_2 \\ x_2 &= \left(\frac{mgk \sin x_1}{I + mk^2} \right) x_2 + u \\ \dot{\sigma} &= \left(\frac{mgk \cos x_1}{I + mk^2} \right) x_2 + u\end{aligned}$$

Now by using the above equations, observer states are given below,

$$\begin{aligned}y &= x_1 \\ \hat{x}_1 &= x_2 + G_1(y - x_1) \\ \hat{x}_2 &= \frac{mgk \sin x_1}{I + mk^2} + \frac{1}{I + mk^2} \tau + G_2(y - x_1) \\ \hat{\sigma} &= \left(\frac{mgk \cos x_1}{I + mk^2} \right) x_2 + G_3(y - x_1)\end{aligned}$$

By using the figure 4.2 above equations becomes,

$$\begin{aligned}\hat{x}_1 &= x_2 + G_1(y - x_1) \\ \hat{x}_1 &= 11.8829 \sin x_1 + 0.0205 \tau + G_2(y - x_1) \\ \hat{\sigma} &= (11.8829 \cos x_1) x_2 + G_3(y - x_1)\end{aligned}$$

State space of observer is,

$$\begin{bmatrix} \hat{x}_1 \\ \hat{x}_2 \\ \hat{\sigma} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 11.88 \sin \hat{y} \\ 11.88 \cos \hat{y} \end{bmatrix} - \begin{bmatrix} G_1 \\ G_2 \\ G_3 \end{bmatrix} (y - y_1) + \begin{bmatrix} 0 \\ 0.0205 \\ 0 \end{bmatrix}$$

4.3 Nonlinear Compensator

We utilised the state estimations rather than the actual states while implementing the control law. Because of the plant's nonlinearity, a combined estimator-controller in a loop may have problem in stabilizing the system. Similar to the commands produced by CNS, the estimator provides state estimate. Eq 3.12 gives the definition of the combined controller-estimator, compensator.

$$\tau = -2.38 \sin \hat{x}_1 - 112.4 \hat{x}_2 - 232 \hat{\sigma}$$

4.4 Simulations Results

Implement complete model in MATLAB Simulink along with EHGO observer and compensator which is shown in Figure 4.3. Figure 4.4 shows the simulation result of angular

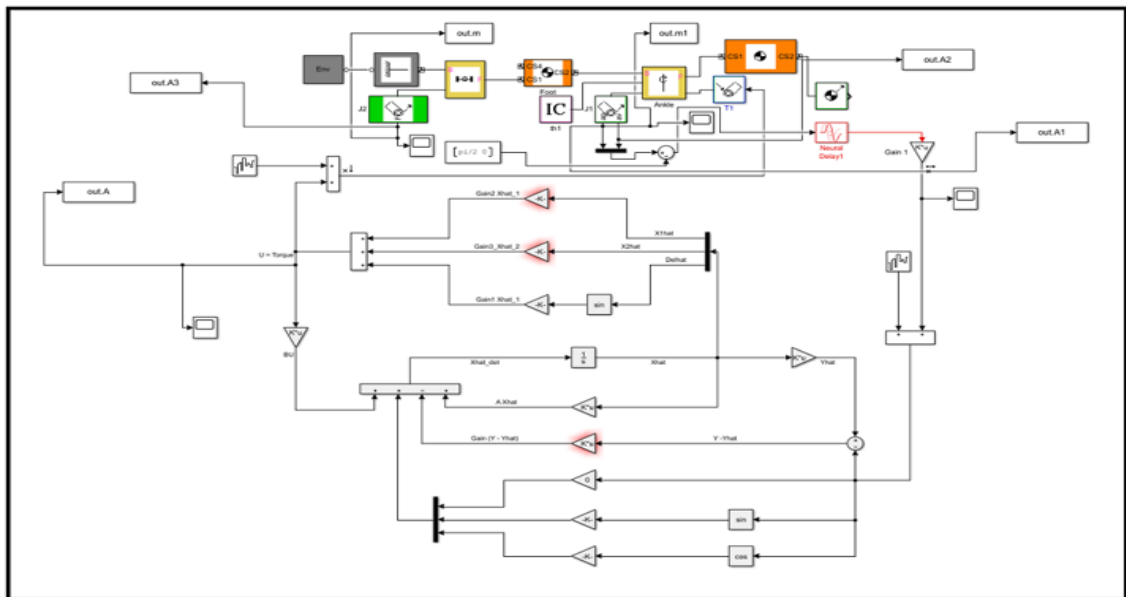


Figure 4.3: Model Implementation in MATLAB SIMULINK

position of ankle joint with respect to time. In start body is unstable then unstable body is stabilized within 1.4 seconds. Now, the figure 4.5 shows the simulation result of angular position of ankle joint with respect to time. In start body is unstable then unstable body is settled down on zero within 2 seconds. Ankle joints torques are show in figure 4.6 and figure 4.7 shows the ground reaction forces. Figure 4.8 show the angular positions of ankle joint with delays of 15ms, 30ms and 45ms in the presence of noise. Nonlinear compensator compensate the noises and delays with controlled input. Figure 4.10 show the angular torques of ankle joint with delays of 15ms, 30ms and 45ms in the presence of noise. Nonlinear compensator compensate the noises and delays with controlled input.

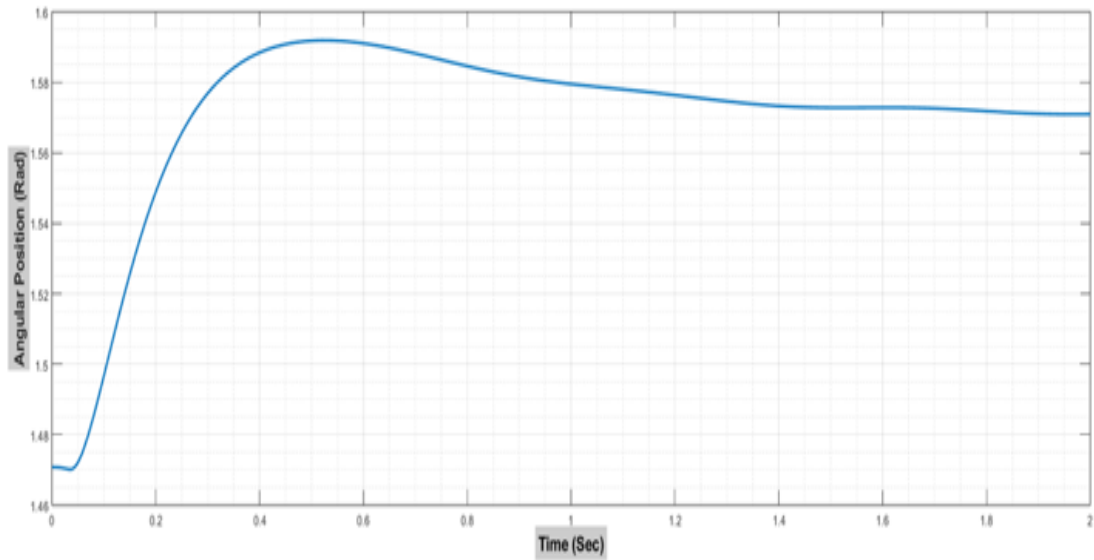


Figure 4.4: Angular Positions at Ankle joint with respect to time

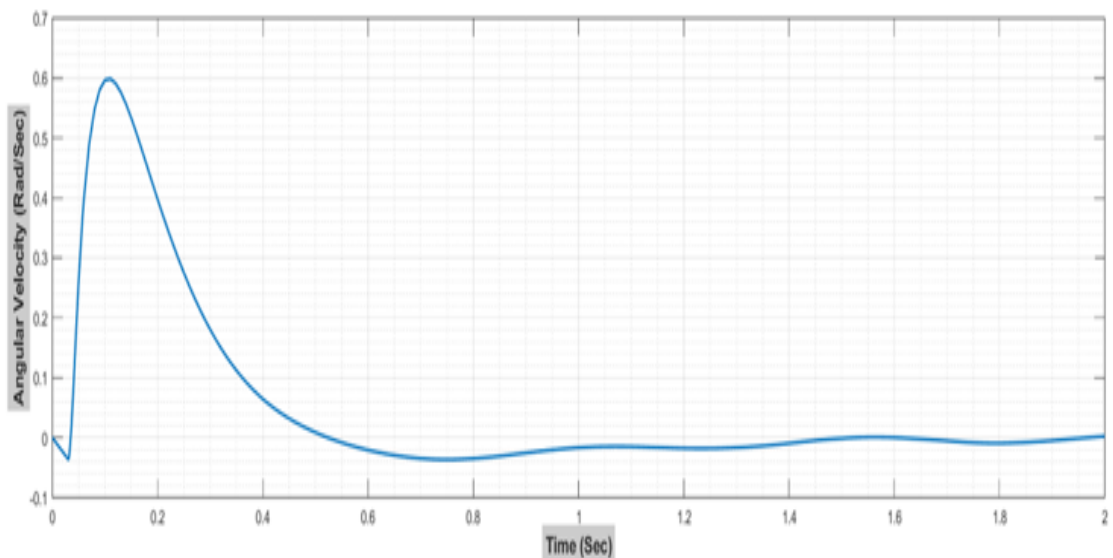


Figure 4.5: Angular Velocity at Ankle joint with respect to time

Nonlinear compensator compensate the noises and delays with controlled input. Figure 4.10 show the angular torques of ankle joint with delays of 15ms, 30ms and 45ms in the presence of noise. While adding different delays in the system, angular positions are settling down at standing equilibrium point within 1.5 to 1.55 seconds as shown in figure 4.8. Moreover, angular velocities are start from zero and settle down at zero it means system not considering any reaction forces as shown in figure 4.9. Although the overshoots are also within the limits. In figure 4.10 torques at ankle joint are also stable at zero. Figure

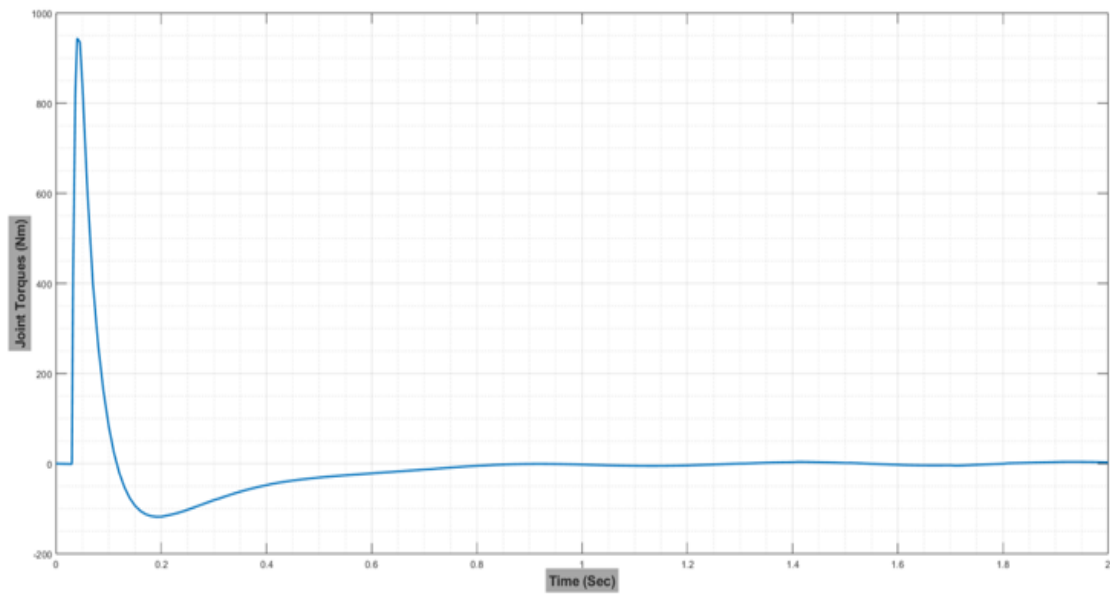


Figure 4.6: Ankle joint torque with respect to time

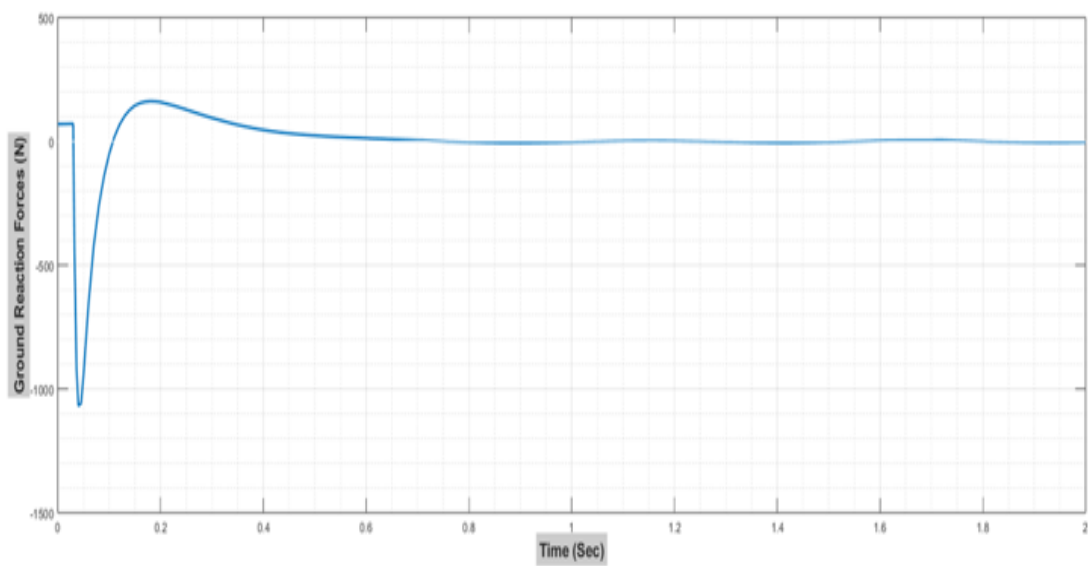


Figure 4.7: Ground reaction forces (GRF)

4.11 shows the comparison of Extended high gain observer with the previous techniques used, so the settling time is reduce to 1.5 seconds and also minimize the overshoot.

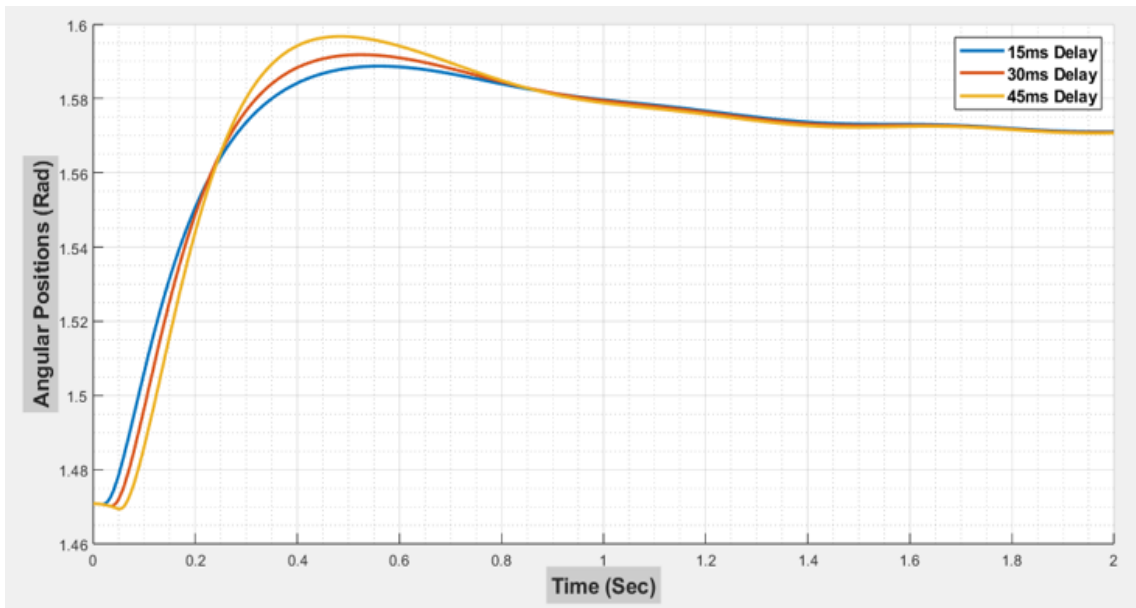


Figure 4.8: Angular Positions of ankle joint with delays

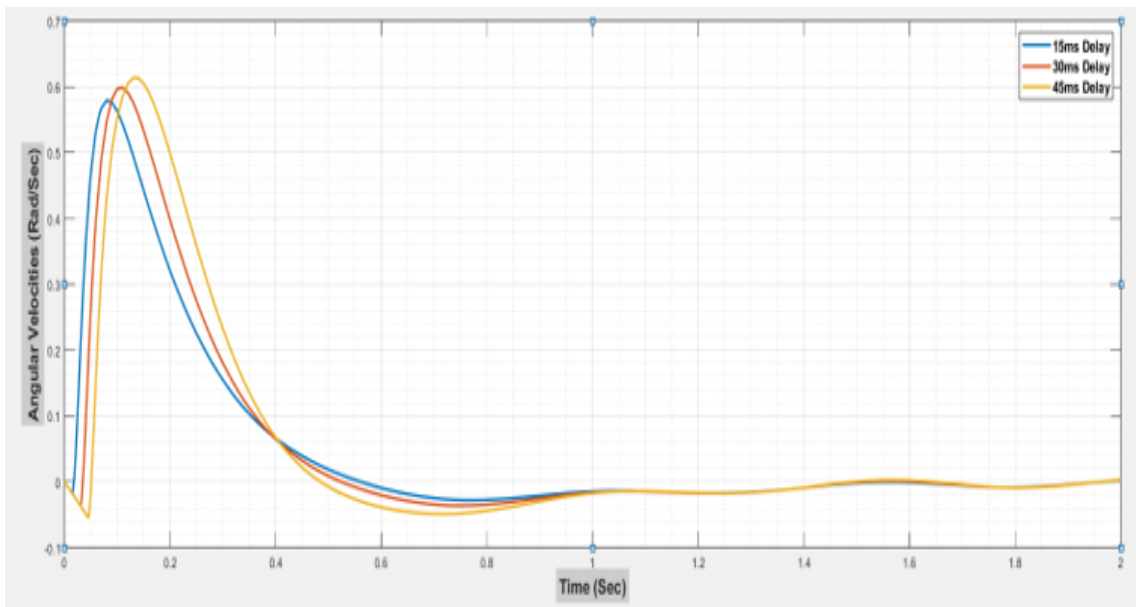


Figure 4.9: Angular Velocities of ankle joint with delays

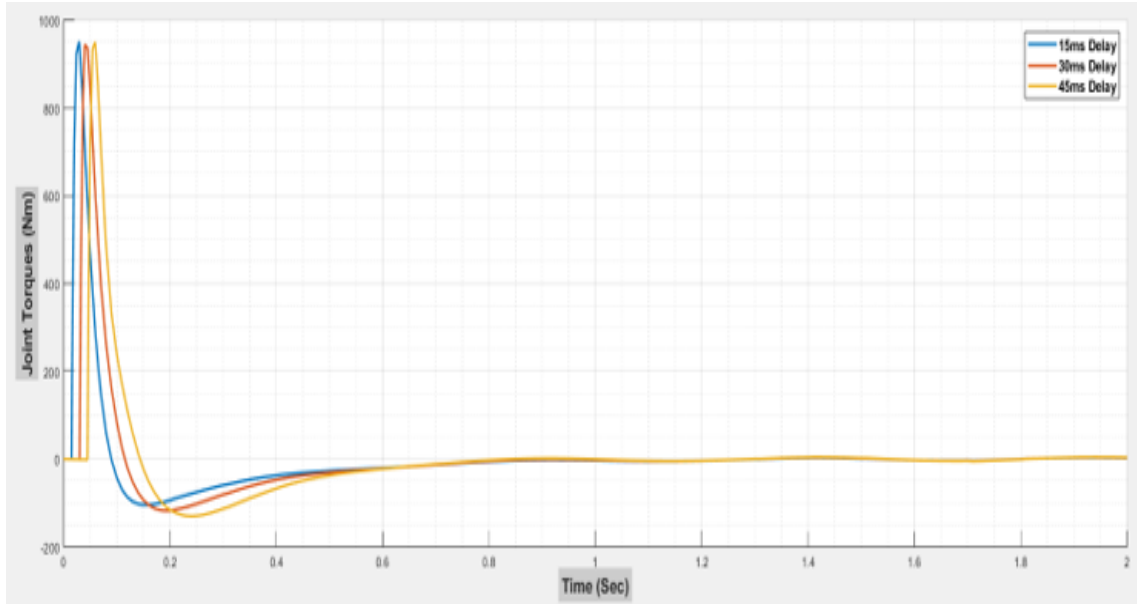


Figure 4.10: Ankle Joint Torques with delays

Approches/Techniques	Settling time	Overshoot
Extended High Gain Observer	1.5 Sec	0.03 Rad
High Gain Observer	2.0 Sec	0.06 Rad
Pade Approximation	2.0 Sec	0.03 Rad

Figure 4.11: Comparison

Chapter 5

Conclusions & Future work

5.1 Conclusion

The simulation model described in this research illustrates an analytical strategy for describing postural recovery motions in a neuro-mechanical form that is physiologically relevant. So, the internal dynamics of a system model. So, in first part of this thesis design an EHGO extended high gain observer (EHGO) which is based on a feedback linearization controller. So, the modeling of CNS will be represented by an EHGO. Basically, EHGO works as a disturbance estimator and a soft sensor of the internal dynamics, respectively. Moreover, AI approach contributes to a better knowledge of the postural control and STS mechanism. Second part of this research focus on traditional machine learning approach used to improve robotic and exoskeleton design. By using head positions of different experimental objects, regression model will predict the positions of ankle, knee, and hip joints. Therefore, on head positions defined as input and position of joints are outputs of the model. In this research supervised learning is used because inputs and outputs are defined or known. So, the techniques used under supervised learning are random forest regression, support vector regression (SVM), decision tree regression (DTR).

5.2 Future Work

- As a temporal lag between the motor command and the formation of muscle torque, we incorporated the dynamics of the muscles and tendons in our study. Musculotendon dynamics can be added to the same model utilizing the Bond graph modelling technique or any other modelling technique as a significant addition in this field. With muscle forces adjusting joint torques, this will add a new level of control. The result of application will further expound on the significance of muscle activation for postural stability and STS movement.

- The inclusion of additional degrees of freedom in the model for more precise simulations can be another significant contribution. To examine biomechanical movements, it is possible to investigate other nonlinear control techniques.
- In this research machine learning approaches are used to predict positions of ankle, knee, and hip joints. So, implement the predicted data in MATLAB Simulink design as a reference values. However, implement other AI approaches to get more accuracy.

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