"ADAPTIVE NEURAL NETWORK METHOD FOR AN EXOSKELETON DEVICE CONTROL"

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Abstract

Patients with brachial plexus injuries or those involving the spinal cord often experience a loss of hand function. They need a tool that can assist them in resuming normal life by regaining some use of their hands. Exoskeleton devices are becoming more popular as a treatment for this condition since they can actuate the fingers of patients, restoring their ability to grip items and carry out other more mundane tasks. In this dissertation, we propose the model of a revolutionary exoskeleton device controlled by an adaptive neural network-based controller. The network of neurons was motivated by the ease with which human hands grip a broad range of items. The gripping forces exerted by a human fingertip on an item in many distinct positions were measured. The neural network is used to estimate the unknown items, and adaptive control is utilized to realize the adaptive features in the unknown environment, in order to realize the stability and high precision control of the control system while facing human interferences. Adaptive control is used to carry out both of these tasks. The user initiates a grip, at which point the neural network uses information about the object's orientation, mass, and dimensions to calculate an estimate of the force needed in each of the five digits to hold it.

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List of Abbreviations

ADL	Activities of Daily Life
FPMs	Flexible Pneumatic Muscles
PM	Pneumatic Muscles
SEA	Series Elastic Actuator
FSR	Field Safety Representative
EMG	Electromyography
SPO	Single Purpose Outlet
IMU	Inertial Measurement Unit
DOF	Degree Of Freedom
RSEA	Rotating Series Elastic Actuator
SNNAC	Single Neuron Network Adaptive Control
INNAC	Improved Neural Network Adaptive Control
ANN	Artificial Neural Networks
RNN	Recurrent Neural Network
LSTM	Long Short, Term Memory
NLP	Natural Language Processing
MCP	Metacarpal Phalangeal joint
PIP	Proximal-Interphalangeal Joints
DIP	Distal Interphalangeal joints
CMC	Carpal-Metacarpal Joints
IP	Interphalangeal-Joints

Chapter 1

Introduction

1.1 Background

The human hand is very versatile, allowing for a wide range of grip types such as cylindrical, palmar, hook, lateral, tip, spherical, etc. The United States is home to an estimated 296,000 individuals with spinal cord injuries and 795,000 people with strokes. There is a correlation between these individuals' impaired hand function and their inability to carry out routine everyday tasks. So, there is a great interest in exoskeleton devices for such cases to rehabilitate the patients. Our project is designed to help those who have suffered a brachial plexus injury and now have impaired hand function as a result of the damage. Even if the patient's elbow and shoulder are in working order, it will be quite challenging to improve their hand's functioning because human hands are bit complex. Therefore, the purpose of the neural network-based device is to assist users in executing fundamental grasping operations in a semi-autonomous manner by activating just the fingers and may be the wrist. To easily grasp items, the gadget requires a well-thought-out design and a strong control algorithm. To the authors' knowledge, very little study has been conducted on controls for exoskeleton systems.

1.2 Problem Statement and Proposed Solution

Stroke is one of the basic cause of disability. It causes functional impairments and disturbance in sensory function. In exoskeleton device rehabilitation, control motion, constrain violation, unknown disturbances and trajectory control are basics. Also because of the nonlinear nature, precision control is difficult to establish.

The proposed adaptive neural network control approach takes uncertainties into account. The adaptive neural network is used to estimate the unknown items, and adaptive control is used to actualize the adaptive characteristics in the unknown environment, in order to achieve stability and high-precision control of the control system while dealing with human interferences.

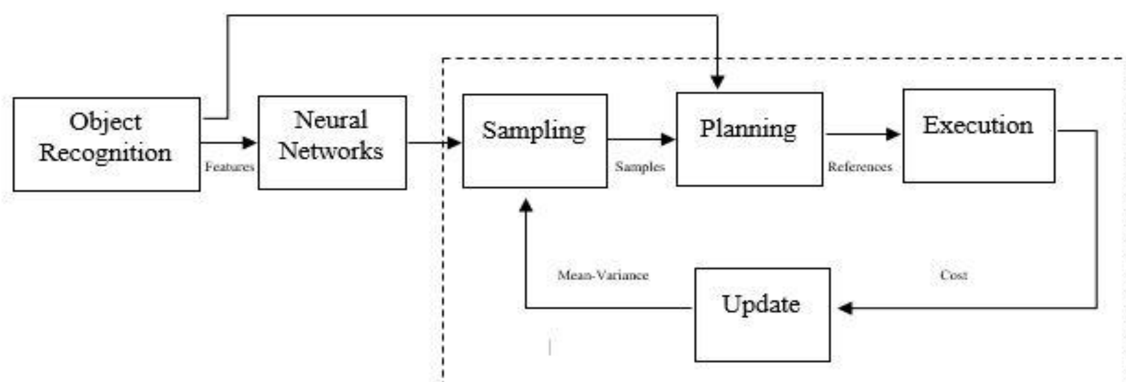


Figure 1-1 Block diagram of proposed model

1.3 Novelty

Despite the fact that the research covers a parameter that has grabbed the interest of most of the researchers and electrical engineers for a long time, there are several limitations in the work done by various authors at different periods. The current research will focus on Adaptive Neural Networks for human exoskeleton device that can help in rehabilitation. Human Hand will used as a part for Neural Network method implementation. In this research, several factors are used simultaneously such as motion tracking, state feedback control, and disturbance observer. So these factors all together can make it more precise and more accurate to work and all factors can be carried out.

1.4 Adaptive Neural Network

The neural network model is based on the single-neuron model. Issues with nonlinear controls and unsure model controls can be successfully solved by its robust learning capabilities and continuous nonlinear function approximation capabilities. To track a device, for instance, Waing et al. [36] presented controller for neural network with a highly nonlinear topology. It has good control effect, according to the simulation results.

The dynamical features of motorized muscular actuators were resolved and the jitter of the adaptable controller under the motion state was reduced by Lee et al. [39], who developed a sliding control technique that utilized neural networks and conducted tracking experiments on the actuator's position and speed. This means that Exoskeletons can be controlled with precision by the neural network. Adaptive neural networks imitate organic neurons. It processes data and demonstrates intelligence by predicting outcomes, spotting trends, and picking up knowledge from the past. It achieves a number of advantages through the creation of interconnected neurons, including a capability for non-linear data processing, robustness in the face of failure, and autonomous maintenance. Adaptive neural networks can use a variety of adaptive strategies to generalize to a specific task.

Chapter 2

Literature Review

2.1.1 Literature Review

A generalized work of neural network-based lower limb control of a robot using disturbance observer by ‘Zhengyuan Hao’ expresses the importance of the intelligent control of exoskeleton device and the importance of the rehabilitation process in functional impairments treatment (Zhengyian Hao, Kang Liu). The focus of this paper is on robotic exoskeleton rehabilitation motion tracking of the lower limb [4].

Similar work has been done by Liang Ding, in which the focus had been made on a full-state constrained wheeled mobile robotic system. Here adaptive neural method has been implemented for tracking control. Neural network and Lyapunov function have been used for estimating unknown functions and the driving effectiveness of the wheeled mobile robotic system is optimized [1].

Another work has done on neural network method for flexible pneumatic muscles. The author focuses on position control in order to do successful robotic workout therapy. Here again nonlinearity and hysteresis of flexible muscles are solved through neural network method. To achieve stability, an improved network adaptive control method is used [3].

In another paper work has been done on the exoskeleton system of a function with a motion control algorithm. In highly parallel and strolling modes, the gadget describes user and exo movements, taking into consideration electric drives and supporting surface reactions. Algorithms for managing the motion of the exoskeleton is presented, taking into consideration the center of mass's provided law of motion as well as information concerning throughout the pertinent periods of movement, there is a force connection between each particular leg and the exoskeleton. The mechanism of gravitational control has used in the research for rehabilitation reasons [2].

A neural network is a computer model for neural networks based on the single neuron model. It offers an efficient solution to resolve FPM's numerical control difficulties and issues with imprecise model control. For instance, Waing et al. [14] presented work for controlling neural networks with a highly nonlinear topology to perform robot tracking. The outcomes of the simulation indicate that it has a superior control effect. Robinson et al. [15] suggested an adaptive neural network control method that integrated neural networks and adaptive control. By developing a neural network-based method for sliding mode control and conducting tests on the position and speed of the actuator, Lee et al. [16] were able in order to combat the nonlinear properties of pneumatic muscle actuators. As a result, the neural network effectively controls robots powered by FPMs.

The RML device is the newest exoskeleton invention; it is made up of rigid mechanical linkages connected to series elastic actuators (SEAs)[13,9]. Since the linkages are flexible, the device can bend in accordance with the user's natural bending profile, and the SEAs enable precise force sensing at the fingertips. Since all of the SEAs are fixed to the palm, the device prevents the normal abduction and adduction of human fingers. A rotating series elastic actuator, which would have allowed for measurement of thumb torque, was not included in this iteration of the device.

This paper shows that index and thumb of exoskeleton device are attached to rigid linkages that are powered by motors [14]. The design relies solely on the index and thumb mechanics to accomplish abduction and adduction, as well as flexion and extension. This device employs a crossed parallelogram mechanism to allow for simultaneous rotation of the distal and middle phalanxes and the middle and proximal phalanxes. The concept incorporates three motors into a single finger mechanism and tips the scales at just 0.51kg. 1.1 kg is the total weight of the exoskeleton. This exoskeleton has a relatively low force application capability (only 0-5 N), making it difficult to grab big objects. The large size and weight of this exoskeleton device can be uncomfortable for the user.

The fingers of this hybrid device [15] may all bend or lengthen due to internal wires and motors, but the little and ring fingers are connected to a single motor. Additionally, it contains soft jamming structures that utilize jamming layers that are joined to the tops of all five digits and are powered by a vacuum pump that is connected to tubes. The soft jamming structures become stiff when a vacuum is provided, which facilitates grabbing. Additionally pneumatically actuated are the fingers' adduction and abduction. Additionally, the device's bottom palm has an additional soft structure linked to it to aid with grabbing.

An orthotic hand assistive exoskeleton (OHAE) was created by Baker et al. (2011) to lessen the force of muscles required to grasp objects [20]. The three fingers are its actuated digits, and they are all propelled by cables that are fastened to a glove. The portable, easily manufacturable device has four main sub-systems and is portable. When an FSR sensor is situated at the appropriate fingertip, the actuator motors retract or extend, which saves muscle energy. In order to assess the viability of supervisory systems based on (EMG) input, Peerdeman et al. (2010) developed a prototype for a bionic hand prosthetic modeled on the biomechanical design of the human hand. The grip selection and execution are governed by the myoelectric signals that are gathered and recognized before being sent into the model to direct the actions that realistically replicate the prosthetic hand [26]. The model is put to the test using two different gripping methods on a simple item, demonstrating hand reshaping and flexibility in the fingers and thumb. The results show the exact finger movement. But this study does not involve a dynamic examination of the finger extension; it is left for further investigation. A new design for a thumb exoskeleton device for rehabilitation was put forth by Iqbal et al. in 2010.

The gadget was optimized using normal hand workspace and capabilities. The process involves analyzing typical everyday activities. The optimization findings demonstrate the thumb exoskeleton's functional and ergonomic requirements.

The SCRIPT Passive Orthosis, a novel hand and wrist exoskeleton design, was unveiled in 2013 as a component of the Monitored Rehabilitation Care Utilizing Personal Tele-robotics (SCRIPT) project, It was conducted by an international team of academics from the Netherlands, the USA, the UK, Germany and Italy. The SPO is an arm and wrist orthosis that interacts with incentive games and provides customizable extension support for post-stroke treatment. It is made up of an already-assembled mobile arm support with a palm plate and fingers caps, a wrist-torque transfer mechanism, a torque-producing mechanism, and a variety of sensors, like an IMU, a flex monitor, and a comparator (Amirabdollahian et al., 2014; Ates et al., 2013, 2015). Therapists have tested the model in numerous therapeutic settings and post-stroke patients have used it extensively at home. The developed exoskeleton's biggest drawback is the lack of a controller that can manage the movements to automatically assist stroke sufferers with their orthoses [24].

References, System Name	Movements (Backed)	DOF	Modeling	Main Control Input (Method Used)	Application Field	Special Function
System Supporting Wrist Movement						
Goupora and Kiguachi (2008)	Wrist Bending and Extending	3 DOF	Muscle modeling	Fuzzy controller, Arm torsion, EMG signaling	Retractable orthoses and assistive technology	Multiple muscle (Three), healthy theme
Sasaki et al., (2008), ASSIST	Flexing the wrist	One DOF	No Description	EMG transmission, joint angle, and compression controller	Wearable orthosis; power assistance	One muscular; flexion, subject in good health
Hu et al., (2009)	Flexing and extending the wrist	One DOF	No Description	Surface EMG	static system; therapeutic tool	Four muscles; (TRI), (FCR), (BIC), and (ECR). Stroke affected

Song et-al., (2009), PolyJbot.	Flexing and extending the wrist	One DOF	Muscular modeling	Component pitch and tension, contact EMG, and Controller	Stationary system; rehabilitation device	Two muscles. Post-stroke subjects
			System Supporting Fingers Movement			
Ho et al., (2011), Hand of Hope, RehabRobotics	Flexibility for every finger	Five DOF	No Dsecription	S-EMG	(Orthosis) moveable system; manual therapy	Competitive Framework
Baker et al., (2011), OHAE	Thumb, index, and middle finger extension	Three DOF	No Description	C-Stamp (coded in C)	Moveable System	Finger tracing for improved back drivability
Yang et al., (2016)	5 fingers	14 DOF	Kinematic and dynamic modeling	A microprocessor as a function generator; advance, backward, speed forward, and rapid reverse pulse signals.	Adjustable orthosis; therapeutic apparatus	New filament exoskeleton with no joints
Wei et al., (2013)	5 fingers	14 DOF	Force simulation	Motor controlling	Adjustable orthosis; therapeutic apparatus	Phantom premium

References, System Name	Supported Movements	DOF	Modeling	Main Control Input, Control Method	Type, Field of Application	Stage of development, Special Feature

System Supporting Wrist and Finger(s) Movement

References, System Name	Movements (Backed)	DOF	Modeling	Main Control Input (Method Used)	Application Field	Special Function
Rose et al., (2015) and Pezent et al., (2017) READAPT	Contraction, expansion, rotary, and lateral motions are all possible.	Twelve DOF	Dynamical interaction model	PID actuator significantly attenuated	Adjustable orthosis; therapeutic apparatus	Donning and doffing for impaired subjectand; Open Wrist features
S. Ates et al., (2014; 2013, 2014, 2015, 2017)	Wrist and finger abduction, retraction and range of motion of the thumb	Six DOF	Dynamic simulation; angle calculation based on data from bendable monitors mounted to each finger	Microcontroller to interface sensors with the dedicated PC to assist the user in playing the therapeutic game	Adjustable orthosis; therapeutic apparatus	Working prototype; Interactive game

Hasegawa et al., (2011)	Wrist and finger abduction, retraction, and range of motion of the five fingers	Eleven DOF	Surface EMG	Vibrational potential-based toggling control	Moveable system	No Descriptio n

Chapter 3

Neural Network Controller Design and Control System

3.1 Simulink Model

The figure 3.1 below shows the Simulink model of the exoskeleton device. Different fingers are used with grip position.

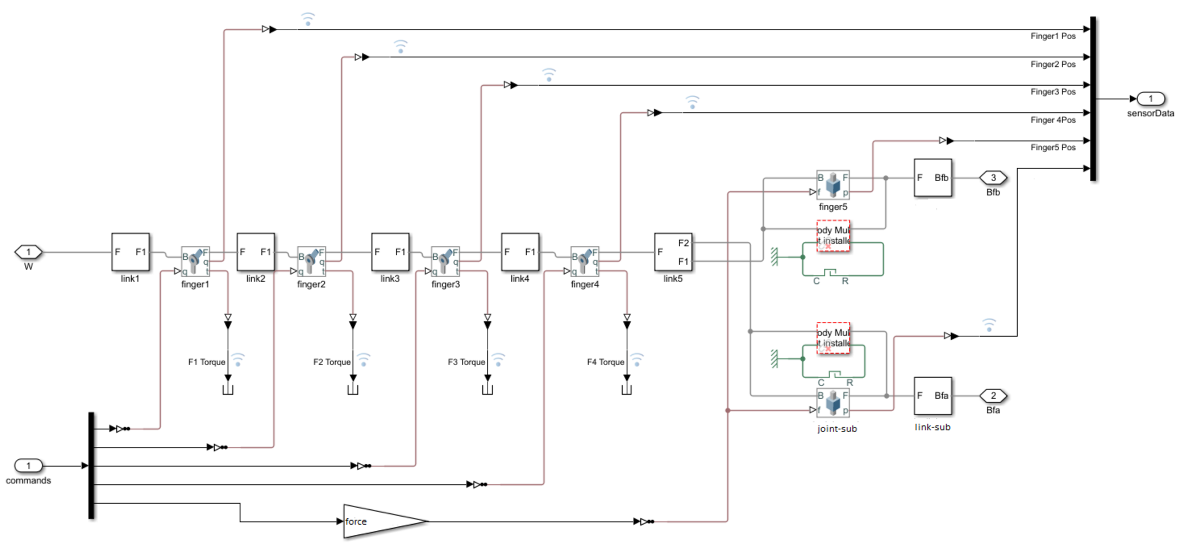


Figure 3.1 Simulation model of exoskeleton device (Fingers)

3.2 Simulation Model Of Exoskeleton Device Joints

The figure 3.2 below shows the Simulink model of the project for joints. Different fingers joints are used to trace trajecteries to show whether the desired path is followed or not.

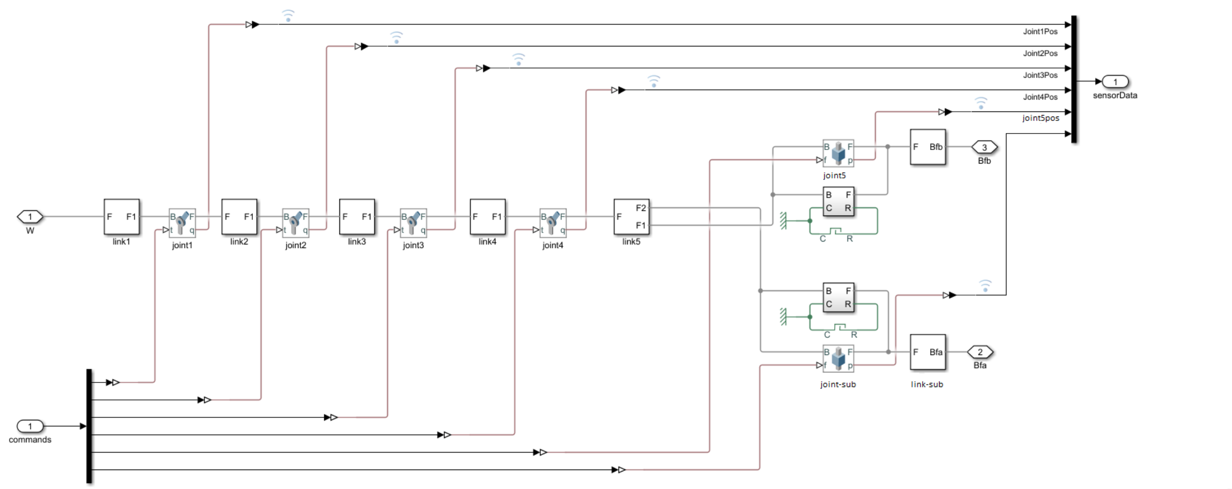


Figure 3.2: Simulation of exoskeleton (joints)

3.3 Methods For Adapting Adaptive Neural Networks

Three alternative methods are used to give adaptive neural networks flexibility. Utilizing an evolutionary approach, one can adapt to a problem's surroundings or change input data. Learning from several neural networks allows the non-evolutionary method to adjust to the learning curve. Additionally, the hybrid approach combines the application of both evolutionary and non-evolutionary methods. These methods enable ANNs to generalize to situations, adjust their model, and learning rate, and input data adaptation as necessary.

3.3.1 Structural Adaptation

In order to identify the best network design, adaptive neural networks can automatically update their models. Finding the best design entails determining how many layers the neural networks will require to function correctly. Three model selection strategies are used to facilitate structural adaptation. The first method searches through all of the previously accessible architectures to choose the model that is most appropriate. The second approach starts with a big, complicated model and progressively reduces it to find the ideal design. The third approach begins with a straightforward model and becomes more complex as learning goes on.

Adaptive neural networks assist in reducing the time needed to process huge datasets with the aid of structural adaptability, and as the operation duration decreases, the time of getting output also decreases. In applications where real-time output is required, structural adaptability is therefore helpful. Robots, for instance, need real-time data processing to move.

Additionally helpful for animation in games, movies, and other applications requiring outstanding animation are adaptive neural networks that employ structural adaptation. Mode-adaptive neural networks are one type of adaptive neural network that, for example, may provide real-time quadruped motion control. The quadruped in the animation can adapt to its changing environment because of the mode-adaptive neural networks, which also enable realistic motion control.

3.3.2 Functional Adaptation

Functional adaptation involves changing the slope of neural network activation functions to minimize output error. The mathematical formulas known as activation functions decide whether or not a neuron in a neural network should fire. By determining whether the neuron's input will be useful for making predictions, and activation functions. They enable neural networks to learn and carry out complex tasks by introducing non-linearity to their output. Artificial neural networks will resemble linear regression models without activation functions. A neural network model's error rate can be decreased with the use of functional adaptation. Functional adaptation is most helpful for classification and recognition tasks since it increases output accuracy.

3.3.3 Parameter Adaptation

During training, parameter adaptation refers to adjusting to shifting weights and biases in the input data. In neural networks, weights are attached to each input. Weights demonstrate the effect that input will have on the result. The influence of input increases with increasing weight. And bias is a constant that is added to the total weights to modify the result in order to best fit the data. A neural network's weights can be modified while being trained to solve a particular problem if it is parameter adaptable. Additionally, neural networks can learn from new weight inputs with the aid of parameter adaptation while maintaining the accuracy of their learning from earlier inputs to a minimum. Swarm optimization, genetic algorithms, and back-propagation algorithms are a few examples of algorithms that can be used to give adaptive neural networks parameter adaptability.

Artificial neural networks encounter a number of significant obstacles that adaptive neural networks can solve. The capacity to adapt makes neural models scalable since they can change their structure and input data at any point during training, which decreases the amount of time needed to train neural networks. Additionally, shorter training times and scalability enable artificial neural networks to overcome their cost-related problems. Consequently, the development of artificial neural networks can be encouraged by the use of adaptive neural networks. Figure 3.3 shows different strategies used by adaptive neural networks.

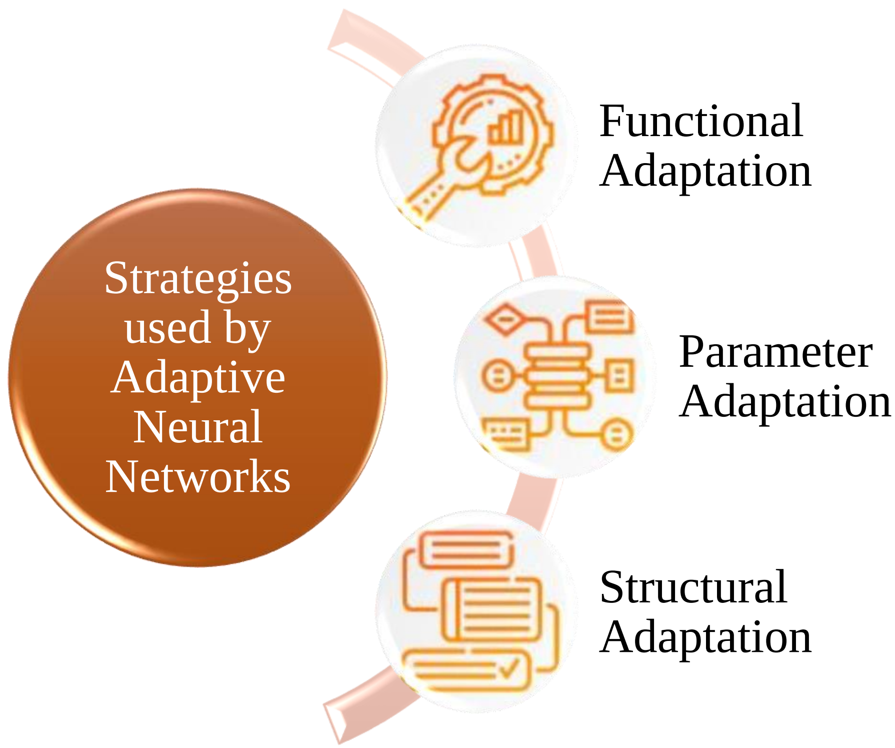


Figure 3.3: Strategies used by Adaptive neural network

3.4 Artificial Neural Networks

Neurons, weights, connections, activation functions, and training are all crucial concepts to keep in mind while talking about ANNs. There is a difference between ANN models, which describe the structure of the network, and ANN algorithms, which describe the computations that lead to the results obtained by the network.

Figure 3.4 shows a graphical illustration of a basic ANN. A layer is made up of neurons that do not communicate with one another. Each layer is denoted by a different hue in Figure 3.4. The red layer represents the input, the blue the hidden, and the green the output. Each sphere in Figure 3.4 is an artificial neuron, and the lines connecting them show how their outputs are fed into the inputs of other fake neurons. Figure 3.4's red neurons represent the sample network's input nodes. All neurons with red color give data to the blue color neurons in diagram. The importance of each input is determined by these connections' weights

$w^{i}_{j,k} = w_{current\ neuron,next\ neuron}$

The blue neurons that are in hidden layer carry out the input vector, and requires adding the supply and bias terms before performing the mathematical operation which is also called the squashing function, and sending the outcome to the output layer. This function, like the sigmoid function, may summarize all inputs times their weights in a straightforward network and condense them to a value between 0 and 1.

$\sigma(z) = \frac{1}{1+e^{-z}}$

$z = f(x, w) = \sum x_i w_i + b_i$ might be used to express the value of z in Figure 3.4.

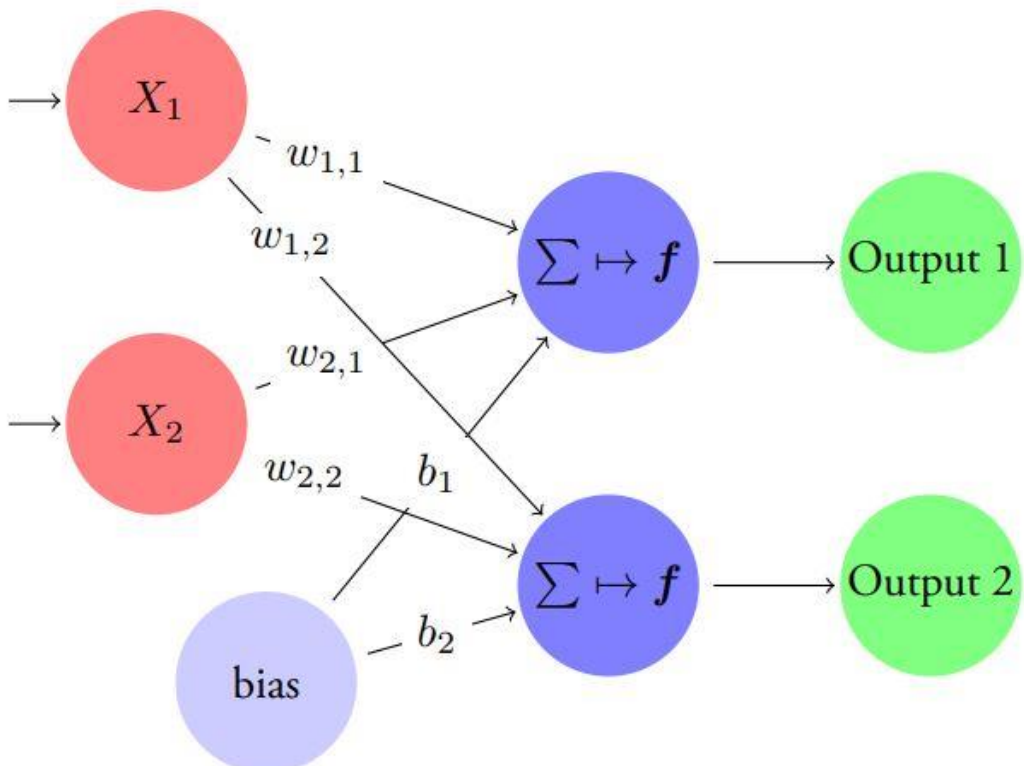


Figure 3.4: Layers of Adaptive neural networks

The weights of the networks are chosen at random, that's why networks needs to train, which means that the weights need to be changed, in order to create the output that is wanted. This is important to keep in mind when thinking about whether or not the results can be repeated. Neural networks are trained using a stochastic optimization technique known as stochastic gradient descent. The algorithm finds a weight set that match your data's input to output mapping function using randomness. Training networks can be divided into two categories: unsupervised and supervised learning. When learning is supervised, a network is trained with a known target result in mind. For instance, in order to match the weights used by the network, an illustration network that will classify photos of horses must be trained on visuals that have previously been identified as such. Unsupervised learning is when the learning process happens on its own.

With this kind of learning, the input data itself is used to force the network to discover patterns, features, and relationships. This may seem like a challenging and drawn-out process. But in a deeper network with a lot of complex data and unknown patterns, relations, and features, it might be the best alternative. This work focuses on Adaptive neural network, which can categorize and forecast data. As a feedforward ANN, the network in Figure 3.4 always pushes data through the layers from left to right in the diagram. In contrast to these ANNs, feedback ANNs have a recurrent design where a layer's output also connects to that layer's input or the inputs of prior layers.

$$f_{activation} = \frac{1}{1 + e^{-z}}$$

Where

$$z = f(x, w) = \sum (x_i w_i + b_i) + y_i \,.\, w_{hi} + output_i \,.\, w_{oi}$$

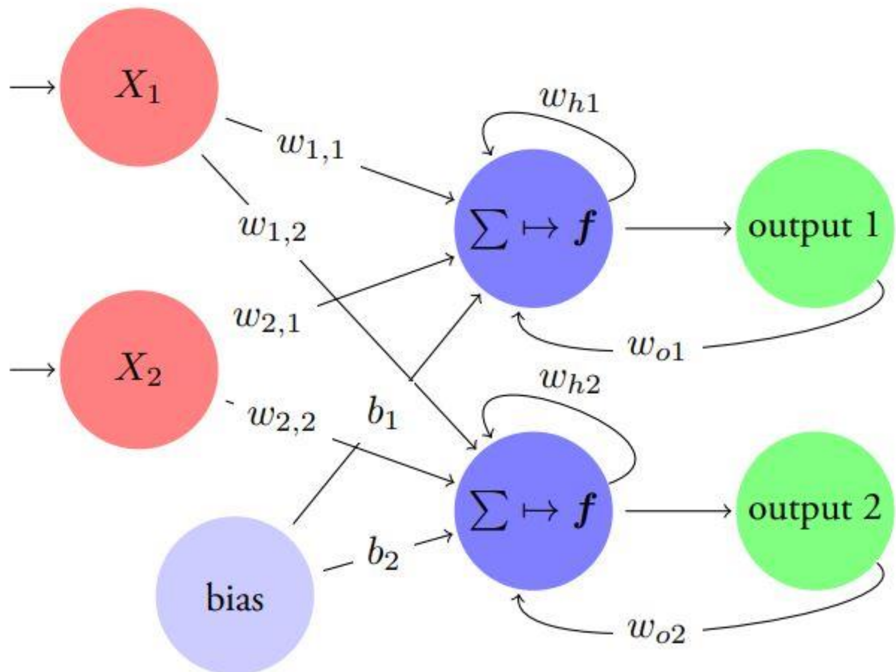


Figure 3.5: Layers of Adaptive neurons with feedback networks

The fundamentals of a feedback network are shared by RNNs, although they concentrate issues inside the time series and sequential tasks domain. Because they are good at predicting the results of subsequent time steps based on the preceding result. Simple RNNs have the drawback of having trouble remembering steps that have been repeated numerous times as well as what is important and what is not. Different details are significant depending on the context. Because we learn and concentrate on the context, humans are exceptionally good at sifting through enormous amounts of information to find the crucial elements; a simple RNN cannot do this. Thus, the development of Long Short-Term Memory (LSTM) units was required. These units can remember and forget values for any length of time, solving the context problem. Figure 3.5 depicts a schematic representation of a traditional RNN.

3.5 Human Hand Exoskeleton

The human hand is made up of a thumb and four fingers. Each finger have three joints. The thumb contains distinct bone structures and distinct joint names.

The functions and names of joints of the index, middle, ring, and little fingers are:

The metacarpal-phalangeal joint (MCP) joins the metacarpal bone to the proximal phalange at the base of the finger.

The middle joint of the finger, the proximal interphalangeal joint (PIP), joins the proximal and intermediate phalanges.

The distal interphalangeal joint (DIP), which joins the intermediate and distal phalanges, is the terminal joint of the finger.

The names of the thumb finger joints are:

The metacarpal and carpal bones at the base of the wrist are joined by the carpal-metacarpal joint (CMC), which is the root joint of the thumb.

The middle joint of the thumb, the metacarpal-phalangeal joint (MCP), joins the metacarpal to the proximal phalange.

The terminal joint of the thumb, the interphalangeal joint (IP), joins the proximal and distal phalanges.

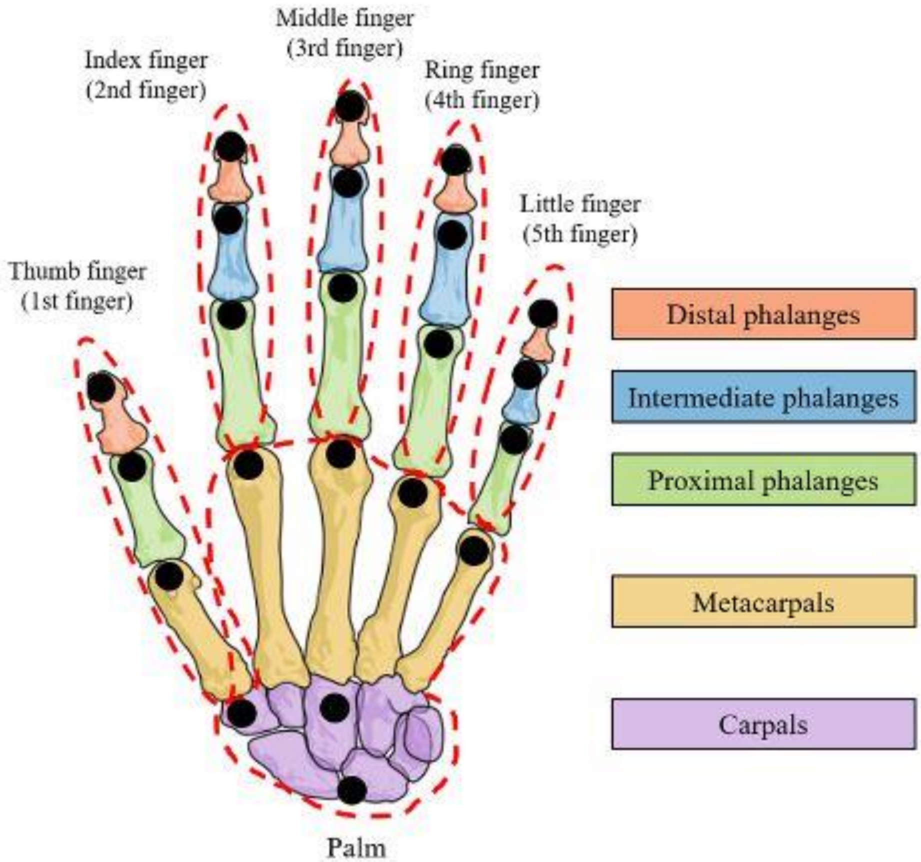


Figure 3.6: Human hand palm with different joints

The carpals and metacarpals of the fingers (index through little) can be taken to be fixed at the wrist joint. The little and index fingers can be used to detect a little amount of metacarpal abduction, which does exist, but it is often a negligible component of the overall hand movement. The three bones that make a finger are the proximal phalange, middle phalange, and distal phalange. Just one phalangeal bone found in the thumb is the proximal and distal phalanges (proximal, middle, and distal phalanges), and the metacarpal moves quite a bit.

3.6 Controller Design Principle

In daily life, humans routinely and readily execute a broad array of grasps. The goal of the control algorithm is to mimic the force distribution produced by a human's fingers while grabbing an item. It has been shown that neural networks may learn new tasks by discovering a sophisticated nonlinear mapping between input and output data. The input, hidden, and output layers of a neural network are composed of interconnected neurons that are weighted. In supervised learning, the network is trained by continuously exposing it to a set of training data and receiving feedback in the form of the desired output data set. Over and over, the network uses backpropagation to fine-tune its weights until it achieves the sought-after precision. After collecting enough data from typical human gripping items of varied shapes and sizes at varying orientations, the network is trained using the same principle

3.7 Control System

3.7.1. Adaptive Neural Network (SNNAC) Algorithm

The algorithm, known as Single neuron network adaptive control (SNNAC) is made first and the output can be expressed as

$$u\,(k) = (k-1) + K \sum_{i=1}^{3} w_i'(k)xi(k)$$

$$w_i' = \frac{wi(k)}{\sum_{i=1}^{3} \mid wi(k) \mid}$$

u (k) represents output signal

The weighted coefficient is represented by $w_i(k)$

K represents proportionality coefficient and K > 0. Selecting K value is crucial. The better the speed, greater will be the K, yet the system will become unstable due to the large overshoot.

$$x1\ (k) = (k)$$

$$x2\ (k) = (k) - (k - 1)$$

$$x3\ (k) = (k) - 2(k - 1) + (k - 2)$$

System input and control output difference at time k can be represented by the value e(k).

$$w_1\ (k) = w_1\ (k - 1) + \eta_I(k)(k)\ x_1(k)$$

$$w_2\ (k) = w_2\ (k - 1) + \eta_P(k)(k)\ x_2(k)$$

$$w_3\ (k) = w_3\ (k - 1) + \eta_D(k)(k)\ x_3(k)$$

η_I = Learning rate of integration

η_P = Learning rate of proportion

η_D = Learning rate of differentiation

And z(k) = e(k)

Combined, the aforementioned equations make up a single neuron adaptive control (SNNAC) system. It is replaced into the aforementioned control system under the assumption that θ d (k) is the reference input signal, and u(k) is the control signal to regulate the device bending motion. θ (k) is the output signal at time k, and e(k) = θ d (k) - θ (k) is angle error. By changing the weighting coefficients, this method—which is straightforward in structure and has a high degree of robustness—realizes the self-adaptive function.

3.7.2 Adaptive Neural Network (INNAC) Algorithm

Higher standards for system and neural network parameters apply to the Adaptive SNNAC algorithm. If the parameters are not appropriately selected, it is easy for the closed-loop control system to diverge. An enhanced Adaptive neural network control mechanism is used to increase the system's stability.

The differential equation of the system can be shown as.

$$\ddot{\theta} = f(\theta, \dot{\theta}) + g(\theta, \dot{\theta})u$$

The ideal control design of second-order nonlinear system is

$$u = \frac{1}{\mathrm{g}(\theta)} [-f(\theta) + \ddot{\theta} d + K^T E]$$

Where, $\ddot{\theta} d$ indicates second derivative of ideal trace trajectory, $K = [k_p, k_d]^T$, $E = [\mathrm{e}, \dot{\mathrm{e}}]^T$ where e is the error of trajectory tracking.

High order terms can be simplified into first order terms by Taylor's formula

$$f\ (u\mathrm{o}) = \ (u\mathrm{o}\ ) + f'\ (u\mathrm{o})(u - u\mathrm{o})$$

Now the differential equation can be shown as

$$\ddot{\theta} = f_1\ (u)\dot{\theta} + f_2\ (u)\theta + f_3\ (u) = (f_1\ (\mathrm{u}_0\ )) + f_1\ '\ (\mathrm{u}_0\ )(u - \mathrm{u}_0\ )\dot{\theta} + (f_2\ (\mathrm{u}_0\ )) + f_2\ '\ (\mathrm{u}_0\ )(u - \mathrm{u}_0\ )\theta$$
$$+ (f_3\ (\mathrm{u}_0\ )) + f_3\ '\ (\mathrm{u}_0\ )(u - \mathrm{u}_0\ )$$

After further simplification, it can be obtained as

$$\ddot{\theta} = f(\theta, \dot{\theta}) + g(\theta, \dot{\theta})\Delta u,$$

$$\Delta u = u - u\mathrm{o}$$

$$(\theta, \dot{\theta}) = f_1\ (u\mathrm{o})^{\cdot} + f_2\ (u\mathrm{o}\ )\theta + f_3\ (u\mathrm{o})$$

$$(\theta, \dot{\theta}) = f_1\ '\ (u\mathrm{o})^{\cdot} + f_2\ '\ (u\mathrm{o}\ )\theta + f_3\ '\ (u\mathrm{o})$$

Radial basic function neural network can be used to approximate function f(θ) in order to gain the stability of the closed-loop system. The following is the neural network algorithm:

$$h_j = exp\,(-\frac{\|x-cj\|^2}{2b^2 j})\;,\; j = 1,2,\,\dots\,, m$$

$$f = w^T h(x) + \varepsilon$$

Where x = [x1 , x2 , ... , xn] ^{T} is the network's input,

While hj is the hidden layer's j neuron's output.

cj = [cj1, cj2,..., cjn] is central vector value of j hidden layer, and h = [h1, h2, … , hn] ^{T} stands for the Gaussian function's output, W for the network's weight, and for its approximation error.

The Adaptive neural network method was developed by combining neural networks with adaptive control, putting system stability and potential unidentified interference into consideration. The control output can be produced as follows by substituting the neural network's output with the function f(θ).

$$u = \frac{1}{g(\theta)}\,[-\hat{f}(\theta) + \ddot{\theta}_d + K^T E]$$

$$\hat{f}(\theta) = \hat{W}^T h(\theta)$$

Among these, W is the estimated value of the ideal weight, and h(θ) is the Gaussian function.

The adaptive law is constructed as follows:

$\dot{\hat{W}} = -\gamma E^T P B h(\theta)$

Where P and B shows setting matrices and γ shows adjustable normal number.

Chapter 4

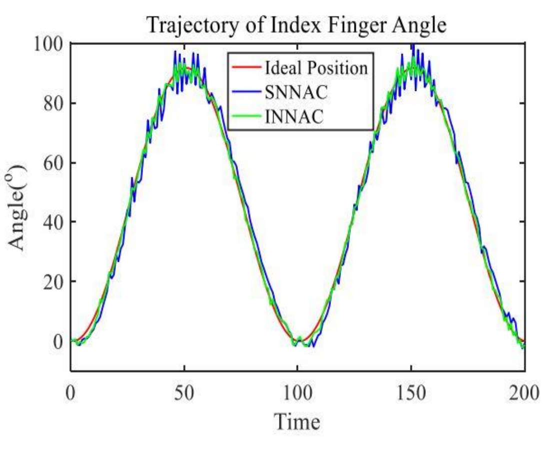
Results

4.1 Results

The trajectories of different fingers have been verified through MATLAB. Thumb, index finger, middle finger, ring finger and little finger, all trajectories are verified.

4.1.1 Thumb

Figure 4.2 below shows the trajectory of the Thumb angle and Trajectory its angle error. Trajectories are shown with ideal position and the path followed after implementing the Adaptive neural network method. The trajectory of the error angle is also shown after implementing the desired method.



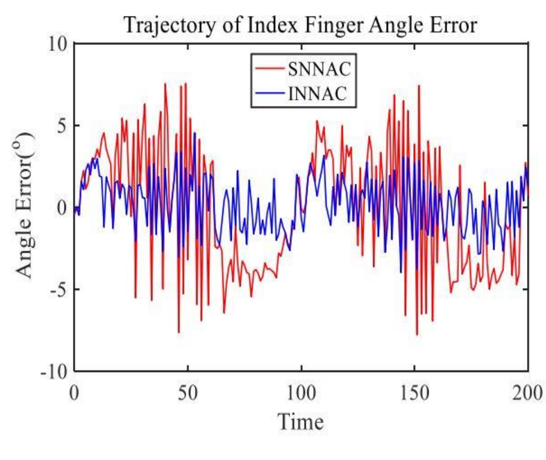


Figure 4.1: Trajectory of Thumb angle and Trajectory of Tumb angle error

4.1.2 Index Finger

Figure 4.2 below shows the trajectory of Index Finger angle and Trajectory of Index Finger angle error. Trajectories are shown with ideal position and the path followed after implementing the Adaptive neural network method. The trajectory of the error angle is also shown after implementing the desired method.

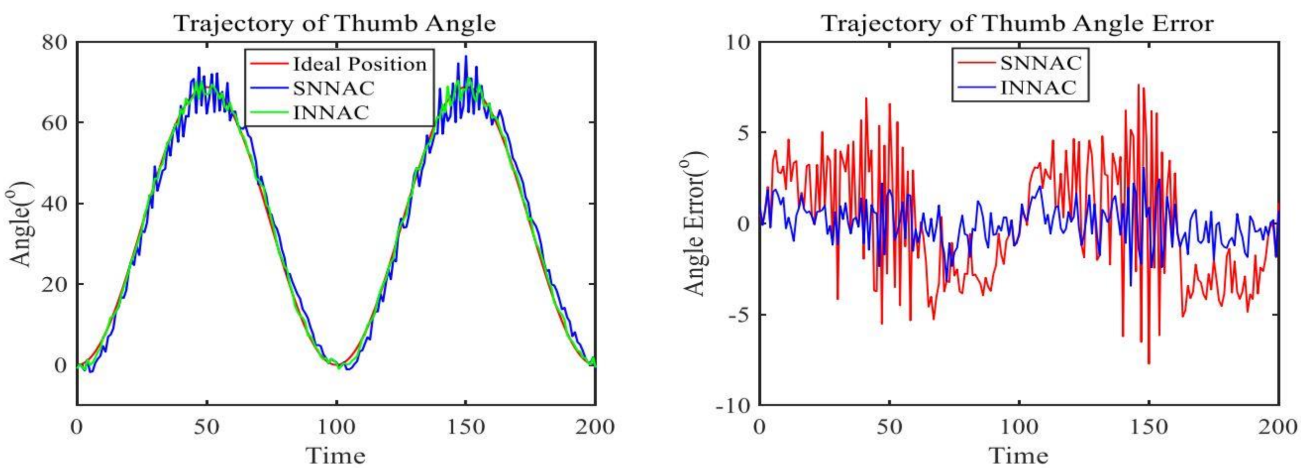


Figure 4.2: Trajectory of Index Finger angle and Trajectory of Index Finger angle

4.1.3 Middle Finger

Figure 4.3 below shows the trajectory of Middle Finger angle and Trajectory of Middle Finger angle error. Trajectories are shown with ideal position and the path followed after implementing the Adaptive neural network method. The trajectory of the error angle is also shown after implementing the desired method.

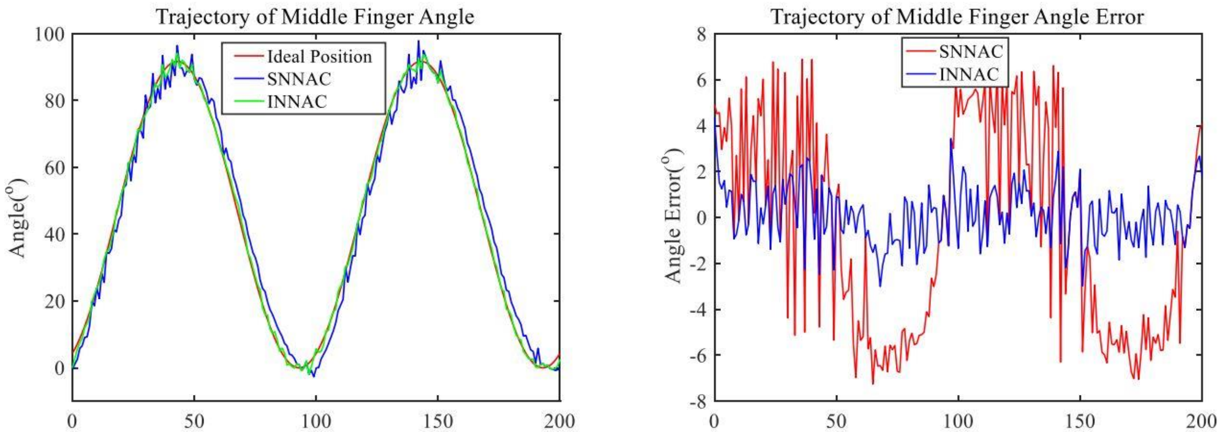


Figure 4.3: Trajectory of Middle Finger angle and Trajectory of Middle Finger angle error.

4.1.4 Ring Finger

Figure 4.4 below shows the trajectory of the Ring Finger angle and the Trajectory of the Ring Finger angle error. Trajectories are shown with ideal position and the path followed after implementing the Adaptive neural network method. The trajectory of the error angle is also shown after implementing the desired method.

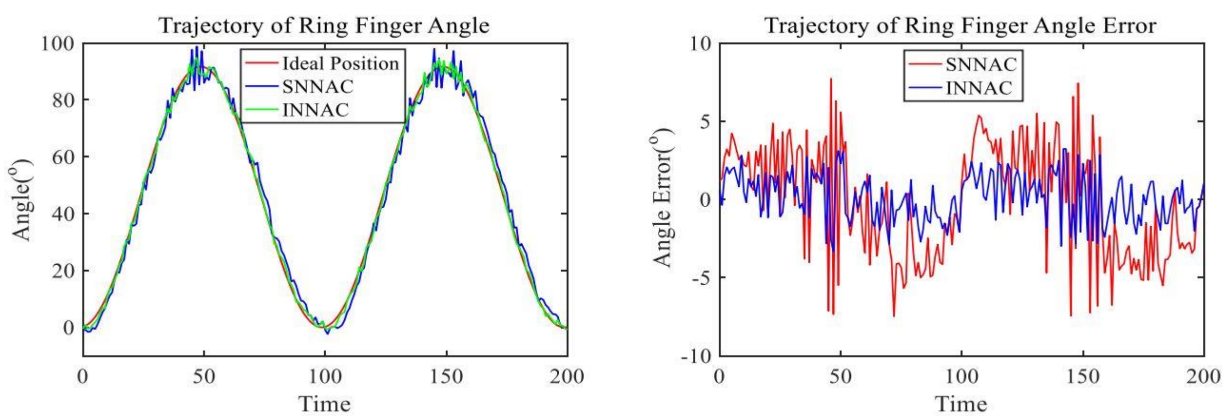


Figure 4.4: Trajectory of Ring Finger angle and Trajectory of Ring Finger angle error

4.1.5 Little Finger

Figure 4.5 below shows the trajectory of the Little Finger angle and Trajectory of the Little Finger angle error. Trajectories are shown with ideal position and the path followed after implementing the Adaptive neural network method. The trajectory of the error angle is also shown after implementing the desired method.

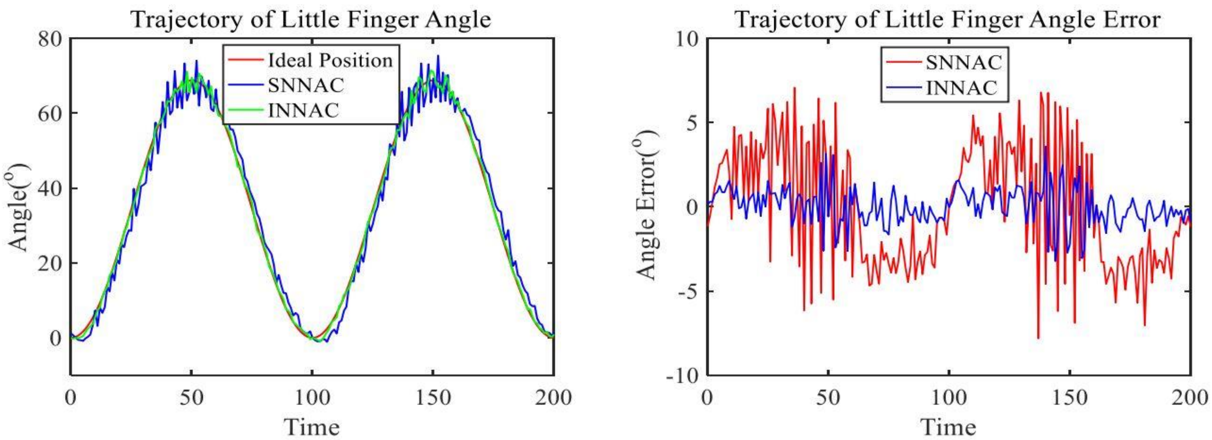


Figure 4.5: Trajectory of the Little Finger angle and Trajectory of the Little Finger angle error.

4.2 Explanation

The five fingers' angle trajectory and error trajectory are shown in the figures. The optimum angle track for each finger is represented by the curve with red color in the angle tracking curve. SNNAC and Adaptive neural network method (INNAC's control) findings are shown as blue and green curves, respectively which are Adaptive neural networks. The Adaptive Neural Network tracking trajectory is more closely related to the ideal trajectory curve and it has a superior controlling effect, according to the experimental results of the angle trajectory of each finger. The curve with red color and the curve with blue color in the error curve graphic, respectively, show the variation in the angle trajectory regulated by SNNAC and Adaptive Neural Network. The results demonstrate that the angle control is unstable, the SNNAC control effect is suboptimal, and the error fluctuates significantly at the curve amplitude. The error fluctuation is less, the Adaptive neural control effect is better and the controlling effect is more reliable

4.3 Trajectory of Angle

Figure 4.6 below shows the trajectory of the angle. Trajectory shows the ideal position and the path followed by the device after implementing Adaptive neural networks. The disturbances are shown which are lagging behind the ideal path.

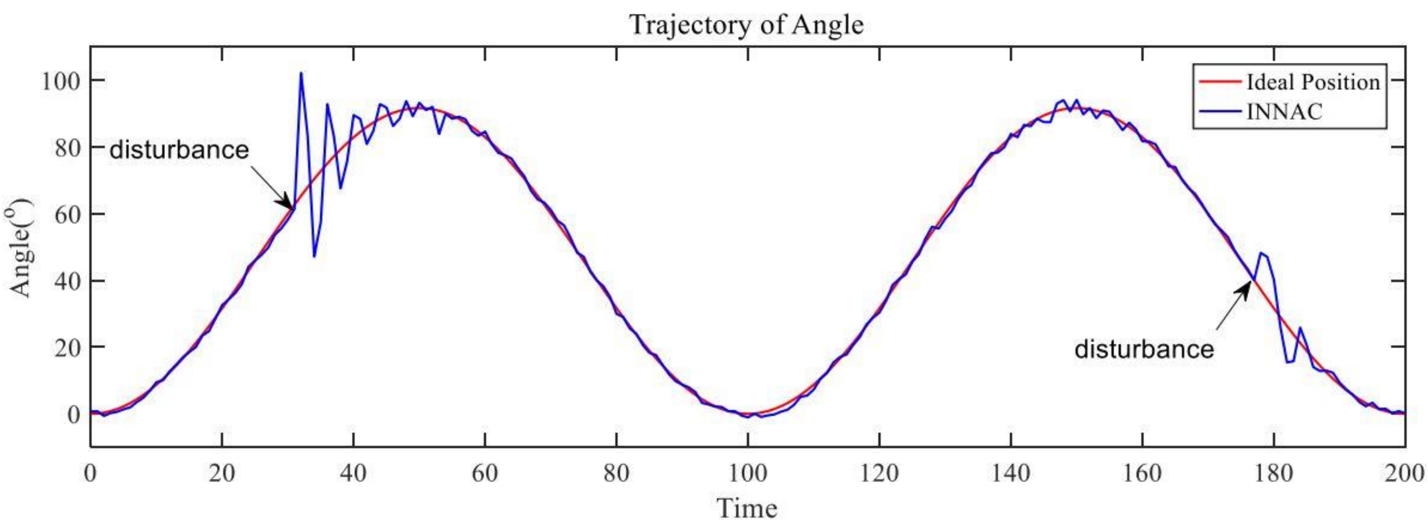


Figure 4.6: Trajectory of angle with disturbances

Chapter 5

Conclusion and Future Work

The conclusion of this thesis is that the Adaptive Neural Network Method of Artificial Intelligence can be used to control exoskeleton devices in an easy and effective manner. Because the trajectory path was successfully followed, it may now be managed by utilizing Adaptive neural networks and Supervisory controls. This method estimates the values of any unknown parameters, and it ensures that the planned trajectory is precisely followed. The overall control performance of the Adaptive Neural technique has significantly improved, and it possesses excellent angle control effect and stability. This method possesses great stability and interference-fighting characteristics, and it can promptly recover to the normal tracking state in the presence of external disturbance. Additionally, it can resist interference well.

Uncertain model control issues and nonlinear control issues can be successfully solved by the robust learning capabilities and continuous nonlinear function approximation capabilities of Adaptive neural networks. The total control performance is improved, and adaptive neural networks have superior angular control effects and stability. This approach has strong stability and interference-fighting capabilities, and it can swiftly recover to the standard tracking state in the presence of external disturbance.

Over the past 20 years, orthoses and exoskeleton technologies have developed significantly. Given the aging population and the rise of individuals with lower limb problems, this is not implausible. A problem still exists in creating robotic exoskeletons that can help several users at once and do so naturally and effectively. Therefore, more perceptive intelligent systems are needed. The motion tasks provided in this thesis are used to evaluate assistive techniques, however, it is necessary to check this approach using two or even more continual tasks with the same device. Few researchers have had the opportunity to work on this topic. It has always been claimed that the exoskeleton user's safety comes first. A clear mechanism that ensures this at the assistive level, nevertheless, needs more research.

Also we intend to implement human-robot interaction and force feedback at some point in the future. The angle control will serve as the foundation for the addition of force sensors, which will offer real-time feedback on the finger joint angle and force signal. This will allow for the successful completion of some more complicated and nuanced rehabilitation training assignments.

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Appendix A

Turnitin Originality Report

AI-Exoskeleton

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