

Clench Strength Prediction for Prosthesis Hand using Surface Electromyogram

By



(Sheikh Shanawaz Mostafa)

A thesis submitted in partial fulfillment of the requirement for the degree of
Master of Science in Biomedical Engineering



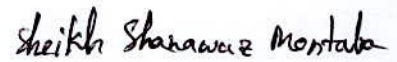
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September 2012

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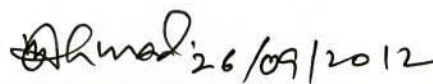


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Abstract

Hand is the main environmental manipulator for humans. Therefore, any accidental lost of hand does a great harm in amputee life. Only choice left that he or she is using prosthesis, which is dated back to ancient time. Due to their usefulness prosthesis is also used in modern days. Now-a-day robotic rehabilitation opens a new era in the field of prosthesis. They are more capable of doing things compared to their ancestors. However, to duplicate the complex work of hand, the robotic hand is needed to complete two basic operations first one is predict the angular displacement and another one is the estimation of force. Estimation of force is essential for instance when drinking from a glass, one needs to apply sufficient grip force to prevent the object from slipping out of the hand. In addition, one needs to control the total torque exerted on the glass such that the glass remains vertical. Usually, the requirements for grip force stabilization allow for some laxity, while the requirements for total torque production are highly specified. The grip force needs only to be larger than the slip threshold and smaller than the force that would break the object. Different researchers used different approach to solve this problem like body-powered prostheses, force-sensitive resistors. Nevertheless, when it comes to rehabilitation of amputee they are not up to the mark in practical field.

Using of Electromyography (EMG) in the robotic rehabilitation shows some hope. Muscle tissue conducts electrical potentials similar to the way nerves do and the name given to these electrical signals is the muscle action potential. A muscle is composed of bundles of specialized cells capable of contraction and relaxation. The primary function of these specialized cells is to generate forces, movements and the ability to communicate such as speech or writing or other modes of expression. The skeletal muscle tissue is attached to the bone and its contraction is responsible for supporting and moving the skeleton. The contraction of skeletal muscle is initiated by impulses in the neurons to the muscle and is usually under voluntary control. Skeletal muscle fibers are well-supplied with neurons for its contraction. This depolarization, accompanied by a movement of ions, generates an electric field near each muscle fiber. An EMG signal is the train of Motor Unit Action Potential (MUAP) showing the muscle response to neural stimulation. There is a clear relationship between force and EMG. The higher the

muscle force, the higher EMG level is developed. Clench force estimation is highly desirable in the field of prosthesis hand. It is one of the most used postures among different types of postures. In this thesis, the author proposes to estimate the clench force using two types of Surface Electromyography (SEMG): rectified SEMG and integrated SEMG. An Artificial Neural Network (ANN) is used to estimate the force from SEMG. For weight adjustment of the estimator Levenberg-Marquardt (L-M) back propagation algorithm is used. The proposed network is trained and tested using SEMG recorded from five subjects. The estimation result clearly shows that integrated SEMG performed 3.53 times better than rectified SEMG in the case of cross correlation coefficient. So integrated SEMG is recommended for clench force estimation. A neural number based experiment is also done to find the optimal number of neurons in hidden layer, which are five neurons as previously described neural network. In addition to that, these result also compared with Support Vector Machine (SVM). Same result is found for integrated SEMG. In the case of rectified SEMG ANN is more suitable than SVM.

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List of Abbreviation

ANN	Artificial Neural Networks
ANS	Artificial Neural Systems
AP	Adductor Pollicis
CORR	Cross-Correlation Coefficient
EMG	Electromyogram
ECG	Electrocardiogram
FSR	Force-Sensitive Resistors
FMG	Force Myography
MSE	Mean Square Error
MUAP	Motor Unit Action Potential
PEs	Processing Elements
RBF	Radial Basis Function
SD	Standard Deviation
SEMG	Surface Electromyography
SVM	Support Vector Machine
SVR	Support Vector Regression

Nomenclature

$K(x_i, x_j)$ = Kernel Function

η = Lagrange multiplier

η^* = Lagrange multiplier

α = Lagrange multiplier

α^* = Lagrange multiplier

$\phi(.)$ = activation function of ANN

w_{ji} = synaptic weight connecting neuron i to neuron j

σ = width of RBF function.

ξ_i = slack variable

σ_2 = Standard deviation

μ = Mean or Average.

ρ = Cross-Correlation Coefficient

CHAPTER 1

INTRODUCTION

1.1 Prosthesis

Prosthesis is a device that replaces missing body parts. Nowadays it is often considered a part of robotic rehabilitation that uses mechanical or robotic device with muscle, skeleton and or nerve system. These are used to assist or enhance victim's life, who lost the body part in accident, disease or any other activity.

The history of rehabilitation engineering can be traced back to the development of functional prosthesis the oldest one (Cairo toe) was found in 2000 in a tomb near the ancient city of Thebes. The Cairo toe is considered a functional prosthesis since it is jointed in three places and according to the archeologists shows signs of wear [1]. In 1508, iron hand made for Gotz von Berlichingen used springs and releases for manipulation. By setting them with the natural hand and using leather straps, it was being capable of holding objects from a sword to a feather pen. Famous surgeon Ambroise Pare also created similar type of hands. Pieter Verduyn developed the first non-locking below-knee prosthesis in 1696 which became the blueprint for current joint and corset devices. In 1868 Gustav Hermann made use of aluminum instead of steel to make artificial limbs lighter and more functional. However, the use of lighter materials wasn't implemented until 1912, when Marcel Desoutter, a famous English aviator, lost his leg in an airplane accident, and made the first aluminum prosthesis with the help of his brother Charles, an engineer. The field of Robotics in Rehabilitation Engineering officially started with the research into Powered Human Exoskeleton Devices in the 1960s.

The process of reading electrical signals is very useful in creating robotic prosthetics. The human body has two forms of electrical signals: produced by the nerves and produced by the muscles are known as bioelectricities that are useful in the development of robotic prosthesis. A myoelectric signal is an electrical impulse that produces contraction of muscle fibers in the body. The term is most often used in reference to skeletal muscles that control voluntary movements. These electrical signals are detected by placing three electrodes on the skin. Two electrodes are positioned so there is a voltage difference between them when a current occurs. The third electrode is placed in a neutral area, and its output is used to cancel the noise that

can otherwise interfere with the signals from the other two electrodes. The output voltage is processed using a device called a differential amplifier, which multiplies the difference between two inputs. The output of this amplifier has much higher voltage than the signals themselves. This higher voltage, which produces significant current, can be used to control electromechanical or electronic devices such as robotic prosthesis.

1.2 State of Art

In 2007, U.S alone had approximately 1.6 million limb losses persons [2]. The permanent loss of an upper or lower limb results in significant challenges in victims' life. A few options like reconstructive surgery or prosthetic devices are available to deal with this loss [3]. Upper limbs of human called hands are not only main physical manipulator of the environment but also have a great influence in the social life. This perfect locomotors system is used for both gross motor skill and fine motor skill. Therefore, loss of hand or hands significantly affects the ability of manipulation.

A new type of rehabilitation named robotic rehabilitation opens a new era in the field of prosthetic device. There are two type of estimation needed for a successful robotic hand one is estimation of joint torques and trajectories and other one is estimation of force. Many researchers have been studying different mechanism and techniques to estimate these parameters proficiently since last two decades. Standard body powered prostheses are controlled by a harness that have proven trustworthy and robust for thousands of amputees [4] but their flexibility is limited by the number of independent control motions practically possible. Another type of system, neurophysiology and biomechanics of muscle, have been studied quite comprehensively in order to illustrate the relations between electromyography (EMG) and various movement behavior. However, complexity of the musculoskeletal made it difficult for using the techniques [5]. Model base approach like the 6-muscle human arm model and 17-muscle monkey arm model [6] have largely unknown nonlinear assumption in each step. However, this type of problem was solved by Yasuharu Koike and Mitsuo Kawato [5] by introducing neural network. Artificial Neural Networks (ANN's) have unique properties, such as generalization and ability to learn from experience and to modify itself according to the changing environment. These properties make ANN's very useful tools for classification and discrimination of nondeterministic and highly disturbed signals or images [7].

Fundamental to human manual dexterity is the ability to precisely control the forces applied by the hand in proportion to the requirements of the task and/or object. Restoring this ability to upper-limb amputees requires dynamic registration of the neuromuscular volition and faithful reproduction of the articulations encoded for the absent hand. There are six types of grip: power, pinch (precision), oblique, lateral, hook, and palm up or palm down. Relatively few studies have been performed to estimate Clench force (power grip). For cording pinching patterns visual feedback system was used by [8]. This visual system actually designed for stroke and other neurological disorders not for amputee. The authors in [9] used force-sensitive resistors (FSR), for estimating the Clench force. The main drawback to FSRs is a result of its spongy resistive material in central component. It takes a while to re-inflate after it been compressed. This re-inflation time is a function of how long and how hard it is pressed. After release, the FSR value will come back to 95% of its initial value almost instantly, and then drift that final 5% over the next 10 seconds. The inner material is also very sensitive to the way it is pressed. It has a non-linear pressure response, which varies with time, temperature, humidity, and even between parts of the same production batch. This makes the FSR a poor choice where accuracy and repeatability are a concern. Finally, FSRs can also be very fragile when frequently placed under high forces. They are made of thin, laminated plastics. This usually results in them coming apart if they are not mounted correctly [10].

The goal of this research was to critically evaluate force myography (FMG) as a representation of dynamic grip force for proportional control for amputee's prosthetic hand. As surface electromyography (SEMG) has a relationship with the force: the higher the muscle force, the higher SEMG level is developed [11]. This research will try to predict clench force for robotic rehabilitation using SEMG without interfering with the human haptic sense like [12]. Authors in [12] tried to estimate pinch force from Adductor Pollicis (AP), Abductor Pollicis Brevis, Dorsal Interosseous muscles. However, these muscles are actually below the wrist level. For natural rehabilitation, the author assumes that the subjects do not have the body parts (amputee), or the subject is unable to use the body parts (i.e. palm). In addition, authors in [12] used a wrist brace but it is impossible for real world application. Therefore, the method used in [12] is impractical in rehabilitation. This research use clench force with two types of SEMG and the electrodes are used above the wrist muscles unlike [12]. Moreover, it may be a common alternative of a force transducer used in [9].

1.3 Objectives

The objectives of this research work are:

- To predict clench strength of arms under voluntary control using ANN.
- To train the ANN with the realistic signal collected using the BIOPAC system.
- To predict clench strength of arms under voluntary control using support vector.
- To evaluate the performance of the proposed method and to compare with the other techniques such as support vectors.
- To present the quantitative and qualitative evaluation of the predicted or estimated signal.

1.4 Contributions

Some original outcomes of this research are listed below:

- A simplified artificial neural network has been developed to estimate clench force without interfering with the human haptic sense.
- The system does not need any fix frame or wrist brace in the SEMG system which means system is more suitable in practical field.
- There is no spongy material in the sensing the SEMG so there is no delay for re-inflation time.
- The SEMG system is fully non-invasive and electrode displacement has almost no effect so non-trained, non-medical related person could use the system.
- The electrodes of SEMG are used above the wrist so amputee patient can use the system.
- The optimum number of neural need for the job is also calculated.
- Suitable EMG among rectified and integrated is found through the experiment.
- Finally, same dataset are used to create a profile in support vector machine and the two results are compared.

1.5 Potential Application of This Research

The scope of this research is very wide-ranging. Some of them are:

- Clench force estimator can be used as force measurement tool without using any muscle model or any force transducer.
- It can be used as a part of manipulator to goal-directed human activities in virtual and augmented environments.
- System learn itself so there will less time and work in rehabilitation program. It can adjust individual user after running some training. Therefore, the patient will feel that the device is custom made for him or her.

1.6 Organization of this Thesis

Chapter 2: Includes the background knowledge of Hand and EMG signal.

Chapter 3: In this chapter, different types of force predicting methods are discussed with reverent advantage and disadvantage.

Chapter 4: Chapter 4 deals with details experimental procedure and used materials and methods in the research.

Chapter 5: In this section, all results are analyzed.

Chapter 6: Finally, the conclusion and further research opportunities are discussed.

CHAPTER 2

HAND and ELECTROMYOGRAPHY

2.1 Hand

A hand is a prehensile, multi-fingered extremity located at the end of an arm or forelimb of primates such as humans, chimpanzees, monkeys, and lemurs. A few other vertebrates such as the koala (which has two opposable thumbs on each "hand" and fingerprints remarkably similar to human fingerprints) are often described as having either "hands" or "paws" on their front limbs.

2.2 Prehension

The word prehension is derived from the Latin term *prehendere*, meaning "to grasp." Prehensility is the quality of an appendage or organ that has adapted for grasping or holding. According to MacKenzie and Iberall "prehension is defined as the application of functionally effective forces by the hand to an object for a task, given numerous constraints. This definition places an emphasis on the task and functional aspects of the problem. The words 'functionally effective' are used to highlight the fact that the forces must be applied within the functional constraints of the task." [13].

A fundamental functional constraint is the establishment and maintenance of a stable grasp. This means that the object not be dropped. The position used by the hand throughout the task must be capable to overcome potential perturbations or take advantage of the expected forces performing on the object. Another functional constraint in some tasks is the ability to operate the object. In order to achieve the duty, the object is moved or motion is imparted to the object, with possible instabilities going on all along the way. The shaping of the hand prior to contact reflects these anticipated task requirements. And physical constraints, include: properties of the objects; forces like gravity and friction; and properties of the arm and hand. For the object, these include such properties as surface compliance, shape, texture, temperature, size, etc.

Prehensility is an adaptation that has afforded species a great natural advantage in manipulating their environment for feeding, digging, and defense. It enables many animals, such as primates, to use tools in order to complete tasks that would otherwise be impossible without highly specialized anatomy. For example, chimpanzees have the ability to use sticks to obtain termites and larva in a manner similar to human fishing. However, not all prehensile organs are applied to tool use—the giraffe tongue, for instance, is instead used in feeding and self-cleaning behaviors.

Examples: Appendages that can become prehensile include: Prehensile feet have evolved many times across many different species, the hands of primates are all prehensile to varying degrees, and the claws of cats are prehensile.

Prehensile tails – Many extant lizards have prehensile tails (geckos, chameleons, and a species of skink).

- Tongue – of giraffes in particular
- Nose – elephants, tapirs
- Lips – Lake Sturgeon, orangutans, horses and rhinos
- Cephalopod arm – arms such as those of octopuses
- Upper Lip- such as those of a Florida Manatee



2.3 Patterns of Prehensile Hand Function

Engineers always want to duplicate prehensile in mechanical devices, and medical scientists and therapists want to help patients in functional hand usage addressed the question of how the human hand works. For example, G. Schlesinger in Germany developed a simple taxonomy in 1919 [14]. It was as a way to classify prehensile functionality for prosthetic hands due to injuries from World War I, as seen in Figure 2.1.

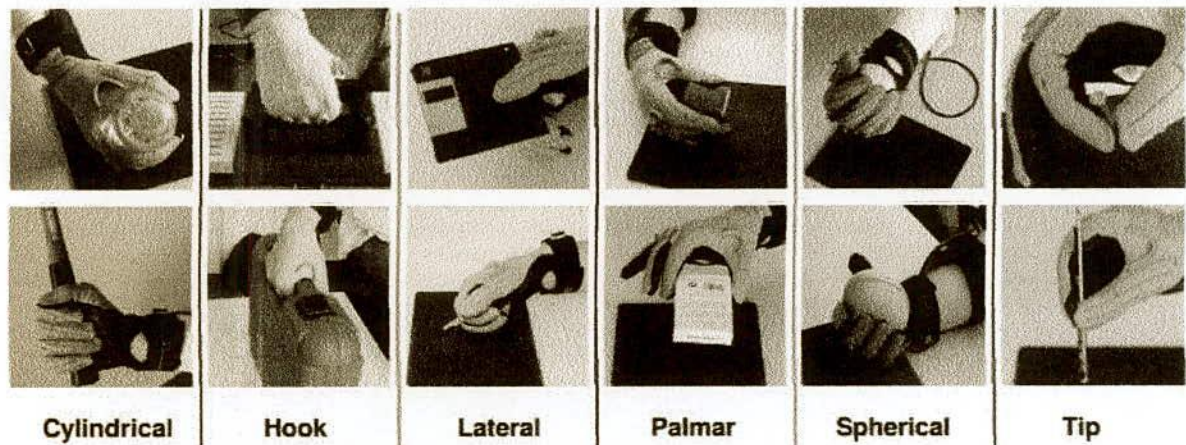


FIGURE 2.1 IMAGES OF SOME OF THE OBJECTS USED DURING THE GRASPING EXPERIMENTS WITH THEIR CORRESPONDING GRASP TYPES

Schlesinger's classification represents one of many attempts that have been made to classify hand postures by researchers from different perspectives for medical, clinical, occupational, and industrial applications. These taxonomies are summarized in Table 2.1. Some classifications are more anatomical, but mainly focused on functionality, particularly for evaluating remaining capabilities after accidents, disease or surgery. Taxonomy offers a new insights into the complexity of human prehension. Yet, across this diverse set, themes are repeated, suggesting the possibility of a unifying view, as will be seen in this section. Selective classifications are considered in order to develop the important roles of hand, object, and task characteristics in the selection of an appropriate, efficient grasp posture.

TABLE 2.1 PREHENSILE CLASSIFICATIONS DEVELOPED IN ANTHROPOLOGY, MEDICINE, BIOMECHANICS, ROBOTICS, AND OCCUPATIONAL THERAPY [13]

Researchers	Posture names	
Cooney and Chao [15]	grasp	tip pinch
	palmar pinch	lateral pinch
Cutkosky [16]	large diameter heavy wrap	4 finger precision grasp
	small diameter heavy wrap	3 finger precision grasp
	medium wrap	2 finger precision grasp
	adducted thumb wrap	disk precision grasp
	light tool wrap	spherical precision grasp
	disk power grasp	tripod precision grasp

	spherical power grasp 5 finger precision grasp	hook, platform, push lateral pinch
Elliott and Connolly [17]	palmar grip dynamic tripod pinch squeeze twiddle rotary step linear step	rock radial roll index roll full roll interdigital step palmar slide
Griffiths [18]	cylinder grip	ball grip
Iberall et al. [19]	palm opposition pad opposition	side opposition
Jacobson and Sperling [20]	coding system for fingers, finger positions, finger joint longitudinal axis with respect to the hand positions, contact surfaces, and orientation of object's	
Kamakura et al. [21]	power grip standard power grip-index extension power grip-stal power grip-extension parallel mild flexion grip tip prehension surrounding mild flexion grip	parallel extension grip tripod grip tripod grip-var. 1 tripod grip-var. 2 power grip-hook lateral grip adduction grip
Kapandji [22]	cylindrical palmar spherical palmar digito-palmar sub-terminal pollicis-digital terminal pollicis-digital sub-terminalo-lateral pollicis-digital inter digital latero-lateral tri digital grips	tetradigital-pulp & side tetradigital pulp to side tetradigital by pulp pentadigital-pulp & side panoramic pentadigital pentadigital cleft Directional grip. gravity-dependent grips dynamic grips
Kroemer [23]	disk grip collect enclosure	lateral grip precision or writing grip

	Power grasp pinch or pliers grip tip grip	hook grip finger touch palm touch
Landsmeer [24]	power grasp	precision handling
Lister [25]	span Power grasp precision pinch pulp pinch	chuck grip key pinch hook grip flat hand
Liu and Bekey [26]	power grasp cylindrical grip span precision pinch	pulp pinch chuck grip lateral pinch hook grip
Lyons [27]	encompass grasp precision grasp	lateral grasp
McBride [28]	palm, digits grasping whole hand grasping	thumb, finger grasping
Napier [29]	power grip precision grip	combined grip hook grip
Patkin [30]	power grip external precision grip internal precision grip	pinch grip double grip (ulnar storage)
Schlesinger [14]	open fist cylindrical grasp close fist cylindrical grasp spherical prehension palmar prehension (pincer) tip prehension lateral prehension hook prehension	Cylindrical w/ add. thumb flat/thin (2 finger) pincer three-jaw chuck nippers prehension large (5 fingered) pincer
Skerik et al. [31]	power grip two point palmar pinch three point palmar pinch	tip pinch hook grip link grip (lateral pinch)
Slocum and Pratt [32]	grasp pinch	Hook

Sollerman [33]	diagonal volar grip spherical volar grip pulp pinch transverse volar grip	tripod pinch lateral pinch extension grip five-fingered pinch
Taylor [34]	palmar prehension (3 jaw chuck) tip prehension	lateral prehension

2.4 Hands as Tools

Schlesinger (1919) [14] put forth a now classic taxonomy that was developed to capture the versatility of human hands for designing functionally-effective prosthetic hands (see Figure 2.1). He used tools and fasteners to describe the special purpose nature of various postures. For example, **simple, regularly shaped objects, symmetrical about an axis internal to the object**, could be held by a pincer or palmar grip, acting much as a set of pliers or as a set of nippers for smaller objects.

A hook grip could be used for suitcase handles and a ring or cylindrical grip could be used for holding a hammer. Seeing the limitations of sensor-based prosthetic design in his time, Schlesinger focused on determining what specific functionality was needed for grasping and holding various objects (e.g. book page, matchbox, pen etc.). From this analysis, Schlesinger devised a minimum set of six grasp postures (see Figure 2.1):

- a) An open fist grip for tools, such as for a hollow cylinder and beer mug. This is the ring function Schlesinger described, and the posture has been called cylindrical prehension [35]. It can also be a closed fist grip for thin objects, such as a shaft.
- b) A posture for spherical objects, such as a ball. The fingers can spread, while the palm can be arched. This is the most adaptable posture and is called spherical prehension.
- c) A posture for flat, thick objects. Movement is provided by fingers for grasping objects such as a large box and a matchbox. This is the pliers function; this posture has been called palmar prehension.
- d) A posture for sharp, small objects, such as a needle, pen, small bearing, and book page. Again, movement is provided by the fingers. This is the nippers function and the posture is called tip prehension.

- e) A posture for thin, flat objects, such as a piece of paper. In this case, movement is provided by the thumb. This posture is called lateral prehension.
- f) A posture for heavy loads, such as suitcases. This is the hook function, and the posture is called hook prehension.

2.5 Anatomy of the Hand

The human hand consists of a broad palm (metacarpus) with 5 digits, attached to the forearm by a joint called the wrist (carpus) [36]. The back of the hand is formally called the opisthenar.

2.5.1 Digits

The four fingers on the hand are used for the outermost performance; these four digits can be folded over the palm which allows the grasping of objects. Each finger, starting with the one closest to the thumb, has a colloquial name to distinguish it from the others:

- Index finger, pointer finger, or forefinger
- Middle finger or long finger
- Ring finger
- Little finger, pinky finger, or small finger

The thumb (connected to the trapezium) is located on one of the sides, parallel to the arm. A reliable way of identifying true hands is from the presence of opposable thumbs. Opposable thumbs are identified by the ability to be brought opposite to the fingers, a muscle action known as opposition (Figure 2.2).

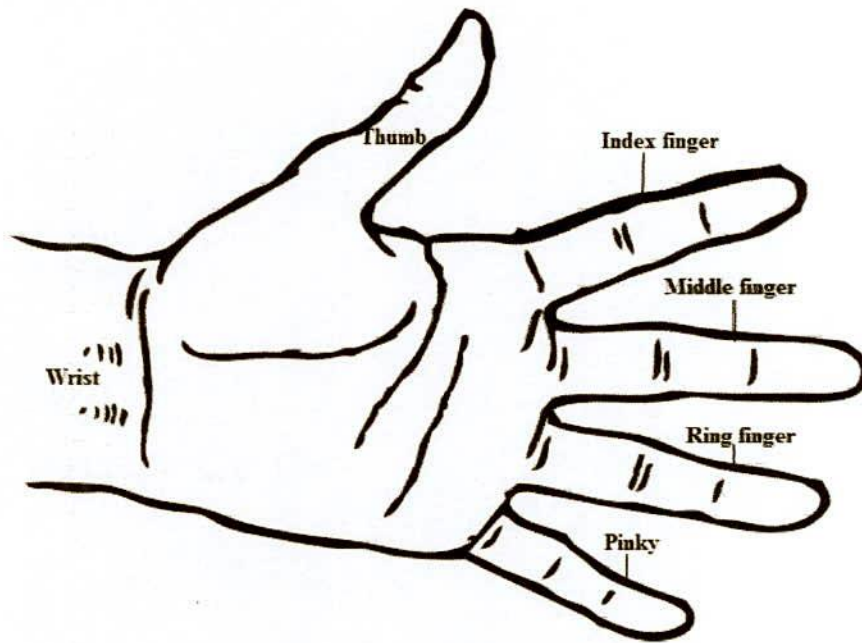


FIGURE 2.2 DIGITS OF HAND

2.5.2 Arm

In human anatomy, the arm is the part of the upper limb between the shoulder and the elbow joints. In other animals, the term arm can also be used for analogous structures, such as one of the paired forelimbs of a four-legged animal or the arms of cephalopods. In anatomical usage, the term arm refers specifically to the segment between the shoulder and the elbow [37] while the segment between the elbow and wrist is the forearm. However, in common, literary, and historical usage, arm refers to the entire upper limb from shoulder to wrist. This thesis uses the former definition.

a) Ulna

The ulna is one of the two long bones in the forearm, the other being the radius. It is prismatic in form and runs parallel to the radius, which is shorter and smaller. In anatomical position (i.e. when the arms are down at the sides of the body and the palms of the hands face forward) the ulna is located at the side of the forearm closest to the body (the medial side), the side of the little finger.

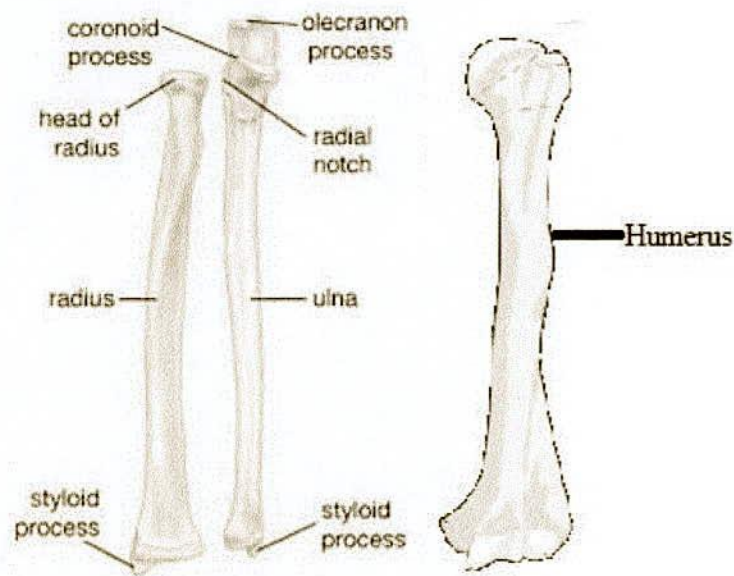


FIGURE 2.3 ULNA, RADIUS AND HUMERUS OF HUMAN HAND

b) Radius

The Radius is one of the two large bones of the forearm, the other being the ulna. It extends from the lateral side of the elbow to the thumb side of the wrist and runs parallel to the ulna (Figure 2.3), which exceeds it in length and size. It is a long bone, prism-shaped and slightly curved longitudinally. The radius articulates with the capitulum of the humerus, the radial notch and the head of the ulna. The corresponding bone in the lower leg is the tibia.

c) Humerus

The humerus is the bone of the arm Figure 2.3. It joins with the scapula above in the shoulder at the glenohumeral joint and with the ulna and radius below at the elbow. The elbow joint is the hinge joint between the distal end of the humerus and the proximal ends of the radius and ulna. The humerus cannot be broken easily. Its strength allows it to handle loading up to 300 pounds.

2.5.3 Hand bones

The human hand has 27 bones Figure 2.4 [38] the carpals or wrist accounts for 8;

- a) The metacarpals or palm contains five;

b) The remaining fourteen are digital bones; fingers and thumb

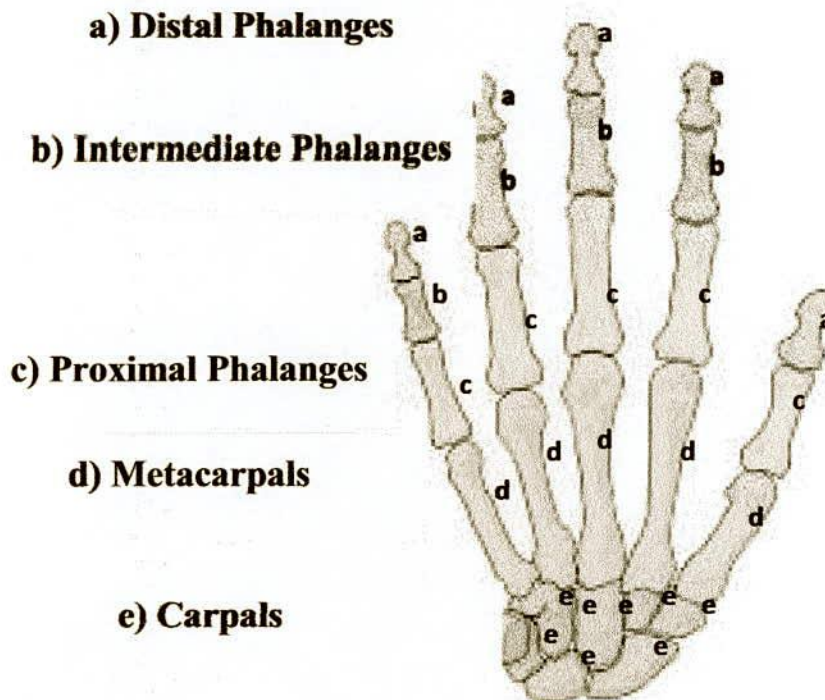


FIGURE 2.4 HAND BONES

Because supination and pronation (rotation about the axis of the forearm) are added to the two axes of movements of the wrist, the ulna and radius are sometimes considered part of the skeleton of the hand.

2.5.4 Muscle

Muscle comes from Latin *musculus*, diminutive of *mus* "mouse" [39] is a band or bundle of fibrous tissue in a human or animal body that has the ability to contract, producing movement in or maintaining the position of parts of the body and is derived from the mesodermal layer of embryonic germ cells. Muscle cells contain contractile filaments that move past each other and change the size of the cell.

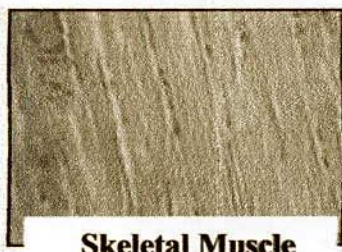
Their function is to produce force and cause motion. Muscles can cause either locomotion of the organism itself or movement of internal organs. Cardiac and smooth muscle contraction occurs without conscious thought and is necessary for survival. Examples are the contraction of the heart and peristalsis, which pushes food through the digestive system. Voluntary contraction of the skeletal muscles is used to move the body and can be finely controlled.

Examples are movements of the eye, or gross movements like the quadriceps muscle of the thigh.

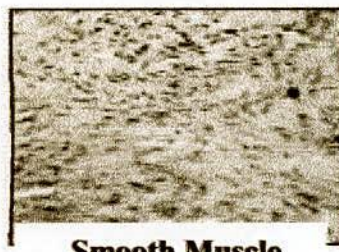
Types of Muscle

They are classified as skeletal, cardiac, or smooth muscles

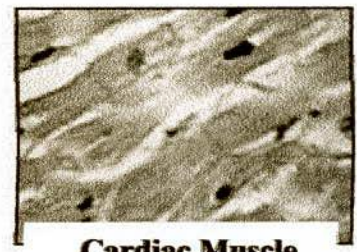
- a) **Skeletal muscle** or "voluntary muscle" is anchored by tendons (or by aponeuroses at a few places) to bone and is used to effect skeletal movement such as locomotion and in maintaining posture. Though this postural control is generally maintained as an unconscious reflex, the muscles responsible react to conscious control like non-postural muscles. An average adult male is made up of 42% of skeletal muscle and an average adult female is made up of 36% (as a percentage of body mass) [40].
- b) **Smooth muscle** or "involuntary muscle" is found within the walls of organs and structures such as the esophagus, stomach, intestines, bronchi, uterus, urethra, bladder, blood vessels, and the arrector pili in the skin (in which it controls erection of body hair). Unlike skeletal muscle, smooth muscle is not under conscious control.
- c) **Cardiac muscle** is also an "involuntary muscle" but is more akin in structure to skeletal muscle, and is found only in the heart.



Skeletal Muscle



Smooth Muscle



Cardiac Muscle

FIGURE 2.5 TYPES OF MUSCLE

2.5.4.1 Superficial Muscles of Anterior Forearm

- a) Biceps brachii
- b) Brachialis
- c) Brachioradialis
- d) Flexor carpi radialis
- e) Flexor carpi ulnaris
- f) Flexor digitorum superficialis

- g) Flexor retinaculum
- h) Palmaris longus
- i) Pronator teres

a) Biceps

In human anatomy, the biceps brachii, or simply biceps in common parlance, is, as the name implies, a two-headed muscle. The biceps lie on the upper arm between the shoulder and the elbow. Both heads arise on the scapula and join to form a single muscle belly which is attached to the upper forearm. While the biceps crosses both the shoulder and elbow joints, its main function is at the latter where it flexes the elbow and supinates the forearm. Both these movements are used when opening a bottle with a corkscrew: first biceps unscrews the cork (supination), then it pulls the cork out (flexion) [41].

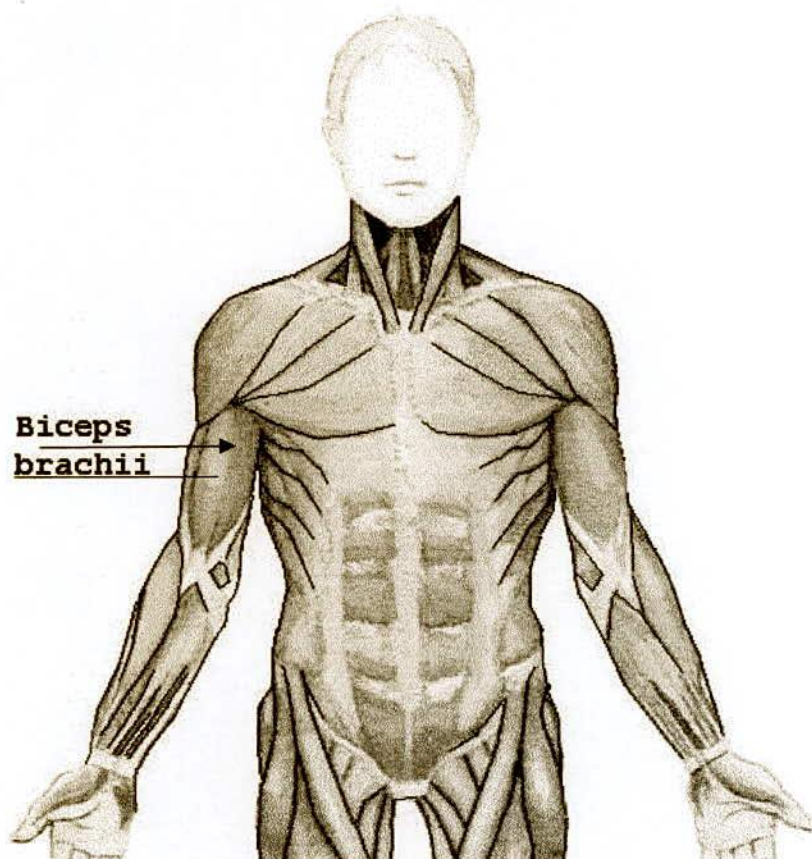


FIGURE 2.6 BICEPS BRACHII MUSCLE

b) Brachialis muscle

The brachialis (brachialis anticus) is a muscle in the upper arm that flexes the elbow joint. It lies deeper than the biceps brachii, and is a synergist that assists the biceps brachii in flexing at the elbow. It makes up part of the floor of the region known as the cubital fossa. The brachialis originates from the lower half of the front of the humerus, near the insertion of the deltoid muscle, which it embraces by two angular processes. Unlike the biceps, the brachialis does not insert on the radius, and therefore cannot participate in pronation and supination of the forearm. It flexes the elbow joint.

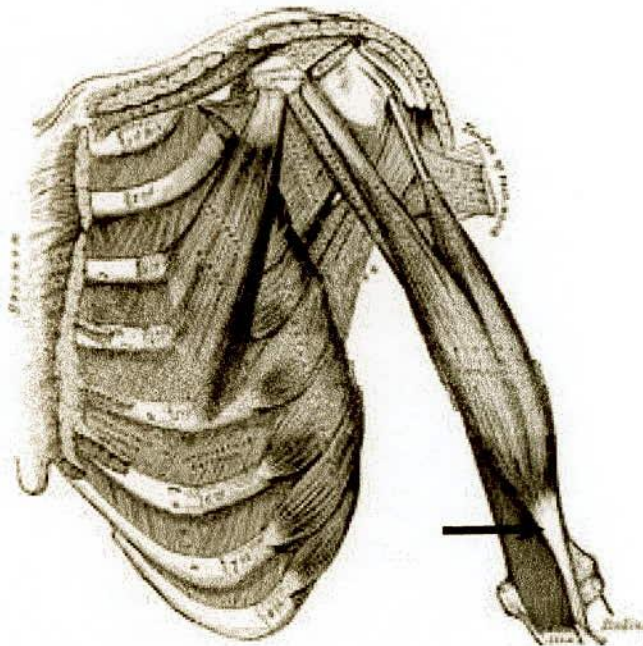


FIGURE 2.7 BRACHIALIS MUSCLE

c) Brachioradialis

Brachioradialis is a muscle of the forearm that acts to flex the forearm at the elbow. It is also capable of both pronation and supination, depending on the position of the forearm. It is attached to the distal styloid process of the radius by way of the brachioradialis tendon, and to the lateral supracondylar ridge of the humerus. Brachioradialis flexes the forearm at the elbow. When the forearm is pronated, the brachioradialis tends to supinate as it flexes. In a supinated position, it tends to pronate as it flexes.

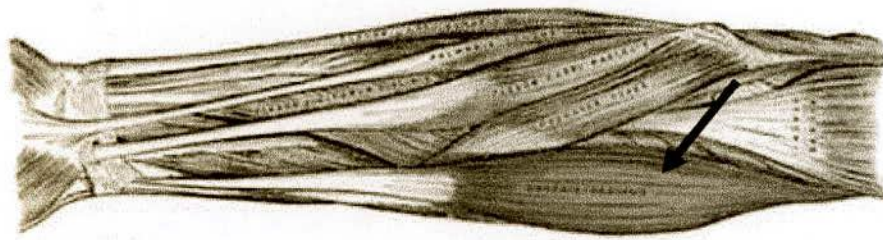


FIGURE 2.8 BRACHIORADIALIS MUSCLE

d) Flexor carpi radialis muscle

In anatomy, flexor carpi radialis is a muscle of the human forearm that acts to flex and (radial) abduct the hand. This muscle originates on the medial epicondyle of the humerus. It runs just laterally of flexor digitorum superficialis and inserts on the anterior aspect of the base of the second metacarpal, and has small slips to both the third metacarpal and trapezium tuberosity.

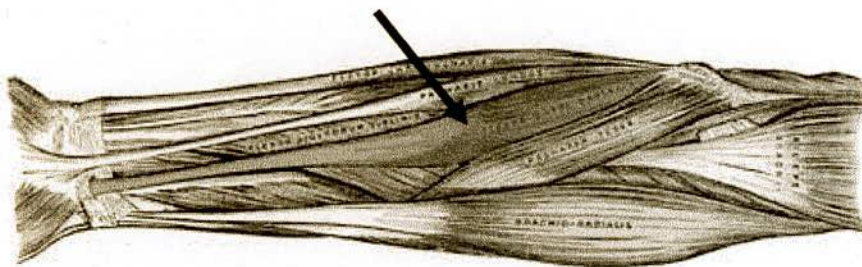


FIGURE 2.9 FLEXOR CARPI RADIALIS MUSCLE

e) Flexor carpi ulnaris muscle

The flexor carpi ulnaris (FCU) muscle is a muscle of the human forearm that acts to flex and adduct the hand. Flexor carpi ulnaris muscle arises by two heads - humeral and ulnar, connected by a tendinous arch beneath which the ulnar nerve and ulnar artery pass. The humeral head arises from the medial epicondyle of the humerus by the common flexor tendon. The ulnar head arises from the medial margin of the olecranon of the ulna and from the upper two-thirds of the dorsal border of the ulna by an aponeurosis. Its insertion is into

the pisiform bone and then via ligaments into the hamate bone and fifth metacarpal bone, acting to flex and adduct the wrist joint.

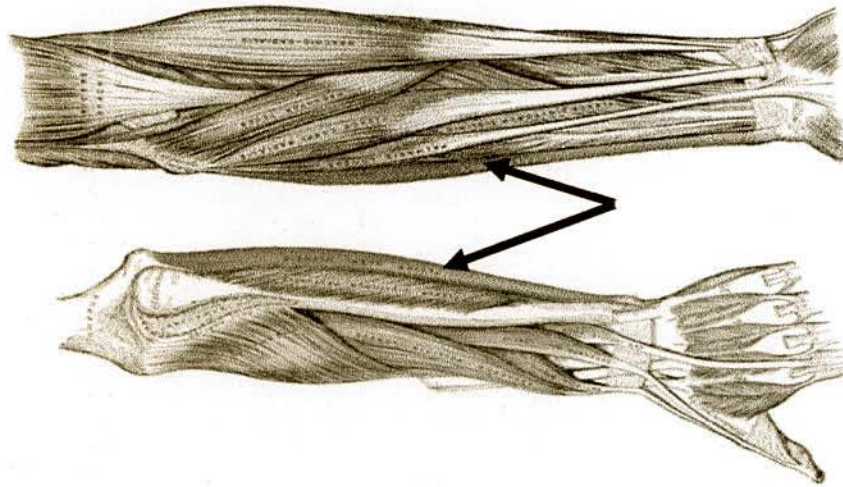


FIGURE 2.10 FLEXOR CARPI ULNARIS MUSCLE

f) Flexor digitorum superficialis muscle

Flexor digitorum superficialis (flexor digitorum sublimis) is an extrinsic flexor muscle of the fingers at the proximal interphalangeal joints. It is in the anterior compartment of the forearm. It is sometimes considered to be the deepest part of the superficial layer of this compartment and sometimes considered to be a distinct, "intermediate layer" of this compartment. It is relatively common for the Flexor digitorum superficialis to be missing from the little finger, bilaterally and unilaterally, which can cause problems when diagnosing a little finger injury.

Origin and Insertion: The muscle has two classically described heads - the humeroulnar and radial - and it is between these heads that the median nerve and ulnar artery pass. The ulnar collateral ligament of elbow joint gives its origin to part of this muscle. Four long tendons come off this muscle near the wrist and travel through the carpal tunnel formed by the flexor retinaculum. These tendons, along with those of flexor digitorum profundus, are enclosed by a common flexor sheath. The tendons attach to the anterior margins on the bases of the middle phalanges of the four fingers. These tendons have a split (Camper's Chiasm) at the end of them through which the tendons of flexor digitorum profundus pass.

Function: The primary function of flexor digitorum superficialis is flexion of the middle phalanges of the fingers at the proximal interphalangeal joints; however under continued action it also flexes the metacarpophalangeal joints and wrist joint. To test flexor digitorum

superficialis is one finger is flexed at the proximal interphalangeal joint against resistance, while the remaining three fingers are held fully extended (to inactivate flexor digitorum profundus).

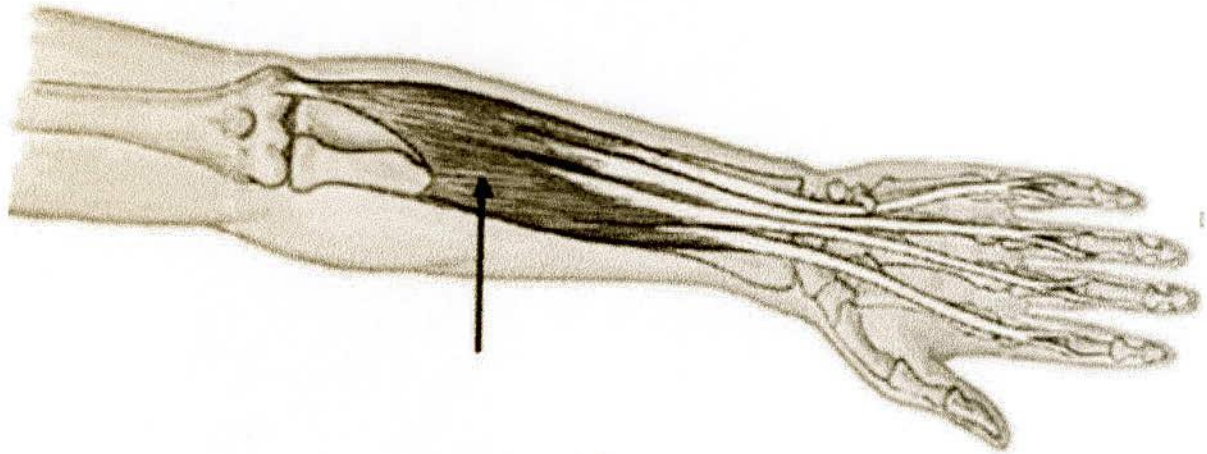


FIGURE 2.11 FLEXOR DIGITORUM SUPERFICIALIS MUSCLE

g) Flexor retinaculum

The flexor retinaculum (transverse carpal ligament, or anterior annular ligament) is a strong, fibrous band that arches over the carpus, converting the deep groove on the front of the carpal bones into a tunnel, the carpal tunnel, through which the Flexor tendons of the digits and the median nerve pass. It is attached, medially, to the pisiform and the hamulus of the hamate bone; laterally, to the tubercle of the scaphoid, and to the medial part of the volar surface and the ridge of the trapezium. It is continuous, superficially, with the volar carpal ligament; and deep, with the palmar aponeurosis. It is crossed by the ulnar vessels and nerve, and the cutaneous branches of the median and ulnar nerves. At its lateral end is the tendon of the flexor carpi radialis, which lies in the groove on the greater multangular between the attachments of the ligament to the bone. On its volar surface the tendons of the palmaris longus and flexor carpi ulnaris are partly inserted; below, it gives origin to the short muscles of the thumb and little finger.

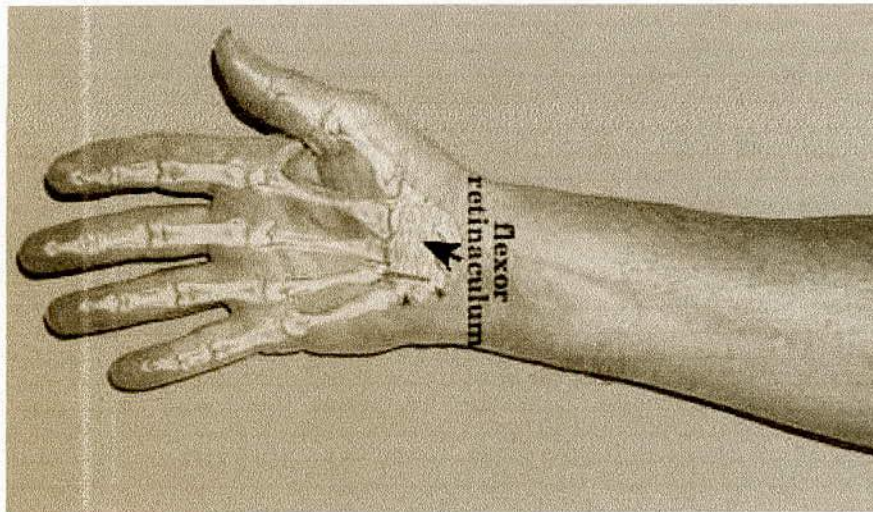


FIGURE 2.12 FLEXOR RETINACULUM

h) Pronator teres muscle

The pronator teres is a muscle of the human body (located mainly in the forearm) that, along with the pronator quadratus muscle, serves to pronate the forearm (turning it so that the palm faces posteriorly (when the body is in the anatomical position)). The pronator teres has two heads--humeral and ulnar. The humeral head, the larger and more superficial, arises from the medial supracondylar ridge immediately superior to the medial epicondyle of the humerus, and from the common flexor tendon (which arises from the medial epicondyle). The ulnar head is a thin fasciculus, which arises from the medial side of the coronoid process of the ulna, and joins the preceding at an acute angle. The median nerve enters the forearm between the two heads of the muscle, and is separated from the ulnar artery by the ulnar head. The muscle passes obliquely across the forearm, and ends in a flat tendon, which is inserted into a rough impression at the middle of the lateral surface of the body of the radius, just below the insertion of the supinator. The lateral border of the muscle forms the medial boundary of the triangular hollow known as the cubital fossa, which is situated anterior to the elbow.

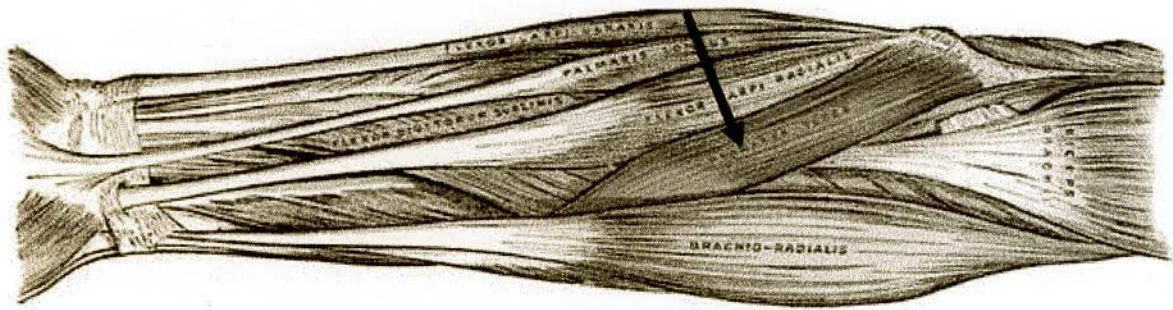


FIGURE 2.13 PRONATOR TERES MUSCLE

i) Palmaris longus muscle

The palmaris longus is seen as a small tendon between the flexor carpi radialis and the flexor carpi ulnaris, although it is not always present. The muscle is absent in about 14 percent of the population, however this varies greatly with ethnicity. Absence of palmaris does not have any known effect on grip strength [42].

Palmaris longus can be palpated by touching the pads of the fifth and first fingers and flexing the wrist. The tendon, if present, will be very visible.

2.6 Electromyography (EMG)

EMG stands for electromyography. It is the study of muscle electrical signals. The development of EMG started with Francesco Redi's documentation in 1666. The document informs that highly specialized muscle of the electric ray fish generates electricity [43]. By 1773, Walsh had been able to demonstrate that Eel fish's muscle tissue could generate a spark of electricity. In 1792, a publication entitled "De Viribus Electricitatis in Motu Musculari Commentarius" appeared, written by A. Galvani, where the author showed that electricity could initiate muscle contractions [44]. Six decades later, in 1849, Dubios-Raymond discovered that it was also possible to record electrical activity during a voluntary muscle contraction. The first recording of this activity was made by Marey in 1890, who also introduced the term electromyography [45]. In 1922, Gasser and Erlanger used an oscilloscope to show the electrical signals from muscles. Because of the stochastic nature of the myoelectric signal, only rough information could be obtained from its observation. The capability of detecting electromyographic signals improved steadily from the 1930s through the 1950s and researchers began to use improved electrodes more widely for the study of

muscles [46]. Clinical use of surface EMG for the treatment of more specific disorders began in the 1960s. Hardyck and his researchers were the first (1966) practitioners to use SEMG [45]. In the early 1980s, Cram and Steger introduced a clinical method for scanning a variety of muscles using an EMG sensing device [45].

EMG is sometimes referred to as myoelectric activity. Muscle tissue conducts electrical potentials similar to the way nerves do and the name given to these electrical signals is the muscle action potential. Surface EMG is a method of recording the information present in these muscle action potentials. The signal is picked up at the electrode and amplified. Typically, a differential amplifier is used as a first stage amplifier. Additional amplification stages may follow. Before being displayed or stored, the signal can be processed to eliminate low-frequency or high-frequency noise, or other possible artifacts. Frequently, the user is interested in the amplitude of the signal. Consequently, the signal is frequently rectified and averaged in some format to indicate EMG amplitude.

A muscle is composed of bundles of specialized cells capable of contraction and relaxation. The primary function of these specialized cells is to generate forces, movements and the ability to communicate such as speech or writing or other modes of expression. Muscle tissue has extensibility and elasticity. It has the ability to receive and respond to stimuli and can be shortened or contracted. Muscle tissue has four key functions: producing motion, moving substance within the body, providing stabilization, and generating heat. Three types of muscle tissue can be identified on the basis of structure, contractile properties, and control mechanisms: (i) skeletal muscle, (ii) smooth muscle, and (iii) cardiac muscle. The EMG is applied to the study of skeletal muscle. The skeletal muscle tissue is attached to the bone and its contraction is responsible for supporting and moving the skeleton. The contraction of skeletal muscle is initiated by impulses in the neurons to the muscle and is usually under voluntary control. Skeletal muscle fibers are well-supplied with neurons for its contraction. This particular type of neuron is called a "motor neuron" and it approaches close to muscle tissue, but is not actually connected to it. One motor neuron usually supplies stimulation to many muscle fibers.

The human body as a whole is electrically neutral; it has the same number of positive and negative charges. But in the resting state, the nerve cell membrane is polarized due to differences in the concentrations and ionic composition across the plasma membrane. A potential difference exists between the intra-cellular and extracellular fluids of the cell. In

response to a stimulus from the neuron, a muscle fiber depolarizes as the signal propagates along its surface and the fiber twitches. This depolarization, accompanied by a movement of ions, generates an electric field near each muscle fiber. An EMG signal is the train of Motor Unit Action Potential (MUAP) showing the muscle response to neural stimulation. The EMG signal appears random in nature and is generally modeled as a filtered impulse process where the MUAP is the filter and the impulse process stands for the neuron pulses, often modeled as a Poisson process [43] [47].

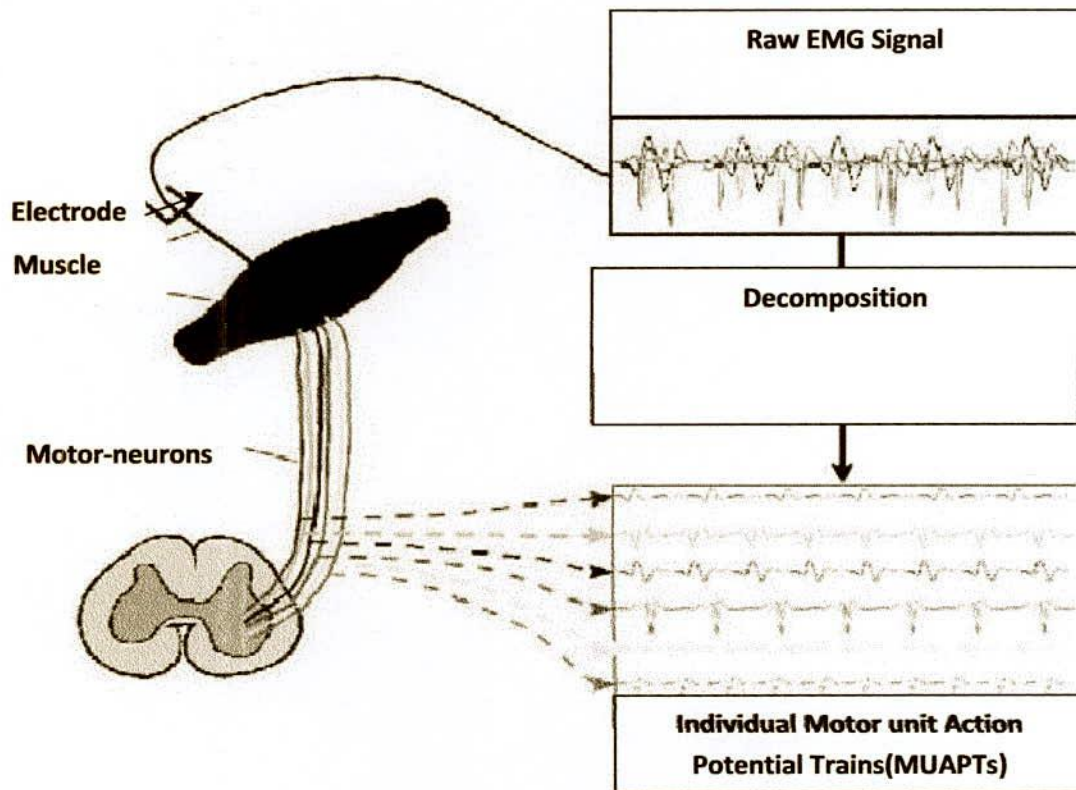


FIGURE 2.14 EMG SIGNAL AND DECOMPOSITION OF MUAPs [47]

CHAPTER 3

FORCE PREDICTION

3.0 Force predictions

The determination of the forces generated by individual muscles during human voluntary movement has become one of the most important research problems in biomechanics and motor control. Norman [48] stated that: "In my opinion, the single most important problem in the study of human motion is the development of accurate, noninvasive methods of calculating individual muscle and ligament force-time histories during normal human movements."

3.1 Force-Sharing Problem

Herzog [49], Herzog and Leonard [50], Li et al. [51], [52], Prilutsky et al. [53] and Zatsiorsky et al. [54] referred individual muscles contributing to a movement task as force sharing among muscles. Latash is classified force-sharing problem as an ill-posed problem. An ill-posed problem exists when a central controller is supposed to make a choice from a theoretically infinite number of solutions while the criteria for making a choice are not explicitly stated. Such problems are similar to attempts to solve one equation with two unknowns; the equation has an infinite number of solutions. The result is a biomechanically underdetermined system.

For example, when a joint is spanned by two or more synergistic muscles, there are an infinite number of different combinations of muscle forces that can produce a desired movement or joint torque. So how a large number of muscles generate a required force or joint torque has received considerable attention [55] .

3.2 Reductionism

The partitioning of muscle and joint forces acting on the musculoskeletal system is referred to as the distribution problem [56]. Unfortunately, determining these forces is not a straightforward process. In the calculation of intersegmental forces, the number of unknown

variables (muscle and joint constraint forces) usually exceeds the number of equations describing the system. The result is a biomechanically underdetermined system, in which there are fewer system equations than unknowns. This is due to the redundancy of the musculoskeletal system, in which more than one muscle often spans a given joint. A common strategy used to solve an underdetermined system is to reduce the number of unknown forces until the number of equations and unknown forces is the same [57]. This is usually accomplished by combining different muscles with similar functions into one muscle group and is referred to as the reduction method. The approach has been used to estimate muscle forces acting at the ankle joint [58], knee joint [59]. The major weakness of this method is that although it provides a mathematically unique solution for the forces in a muscle group, the forces produced by individual muscles are not determined.

3.3 Direct Measurement of Tendon Force

A third method used to examining force sharing among synergistic muscles involves the direct measurement of tendon force [60]. One approach is to measure the strain, which is proportional to force, in a buckle-shaped metal transducer and through which the tendon passes [56]. A second option involves the use of a liquid metal strain gauge placed in parallel with the tendon [61]. Another method is to use optic fiber as a transducer of tendon forces [62]. This method is based on light intensity modulation by mechanical modification of the geometric properties of the optic fiber. The use of direct experimental force measurements to study the interactions of muscles during movement was pioneered by Walmsley et al. [63] and together these studies have given a better understanding of the force sharing between soleus and gastrocnemius muscles for different movement tasks. More recently, direct muscle force measurements in cats were expanded to all muscles comprising a functional group (gastrocnemius, soleus, and plantaris muscles) and a corresponding functional antagonist (tibialis anterior) in order to increase the understanding of force sharing among agonist and antagonist muscles for movements ranging from slow walking to trotting.

The value of direct measurement of tendon force is obvious: it provides the unique ability to study muscle function in vivo and takes movement analysis one-step closer to the neuromuscular system [60]. However, there are several limitations regarding direct tendon force measurement. First, the force measures of a transducer placed on a tendon are questionable, since the transducer is in an environment that is influenced by many other structures surrounding the joint. Second, direct force measurement can only be performed on

selected muscle tendons; Third, tendon response to the force transducer and the length of time the transducer is implanted can influence the output of the transducer. Despite these limitations, direct measurement of tendon forces has contributed to our understanding of the control of the neuromuscular and musculoskeletal systems.

3.4 Optimization

The most common approach used to study the force distribution and sharing problems in human movement is mathematical optimization [64]. Optimization is the process of maximizing or minimizing a desired objective function while satisfying the prevailing constraints. The general concept of optimization in human movement was initially formulated by Weber (1836), who stated that man walks in "the way that affords us the slightest energy expenditure for the longest time and with the best results." Optimization theory has been identified as a useful tool for exploring goal-directed behavior [65]. Typically, optimization techniques are used for two reasons in the study of the control of human movement: 1) to solve the problem of force sharing among synergistic muscles, and 2) to generate movement from the perspective of the neuromotor system. The classifications static optimization and dynamic optimization, respectively, have been used to distinguish between these approaches.

3.4.1 Static Optimization

Static optimization refers to the process of minimizing or maximizing the costs/benefits of some action for one instant in time only. Static optimization methods have been used to estimate muscle forces for the knee, hip, lumbar spine, shoulder, elbow, wrist, and fingers.

In order to solve an optimization problem, it must be formulated in the following way [66] (1) define the cost function, (2) identify the constraint functions, (3) specify the design variables, and (4) set the appropriate bounds for the design variables.

The choice of objective function is very important in static optimization because its minimization or maximization determines the solution to the problem. Indeed, the results are very sensitive to the choice of cost function. An et al. [66] suggest that the objective function must be related to the movement task. Unfortunately, the cost function to be minimized cannot be known a priori and may vary from person to person depending on the demands of the task. The objective functions used to study the force-sharing problem generally fall into two classes: linear and nonlinear optimization criteria.

The estimation of muscular forces using linear objective functions has been obtained by minimizing the sum of muscle forces, by minimizing the muscle stress, or by minimizing the overall muscle activation level. Linear objective functions have been criticized for being incapable of predicting co-activation of synergistic muscles and that the solution is highly related to the number of imposed constraints.

To overcome the limitations of linear cost functions, nonlinear optimization criteria have been used. Nonlinear objective functions can predict co activation of muscles, even without the use of additional constraints. Nonlinear optimization improves muscle force predictions, but this method is usually more involved and less efficient than linear programming [66]. There are several advantages to using static optimization methods to examine the force sharing problem: (1) they are computationally efficient compared to dynamic optimization methods; (2) the contact forces between the body and the environment are typically measured, so the equations can be solved in an efficient distal-to-proximal sequence; and (3) they provide information regarding muscle force and joint contact loading. However, these methods provide limited insight into the underlying neuromuscular control strategy because the performance criterion is solved only at a given instant in time.

3.4.2 Dynamic Optimization

Dynamic optimization refers to the process of minimizing and maximizing the costs/benefits of some objective function over a period; it is sometimes referred to as optimal control. The dynamic optimization process involves using a model that includes the dynamics of a system to find the inputs (e.g., muscle excitation signals) and all outputs (e.g., forces) that maximize the performance of a task. Dynamic optimization has been used to analyze such activities as locomotion [67], and arm movements [68].

The advantage of the dynamic optimization approach is that it parallels the problem that must be solved by the CNS during goal-directed voluntary movement. Dynamic optimization methods predict the muscle excitation signals that produce a given movement. However, there are several limitations to dynamic optimization modeling. First, although the concept of dynamic optimization is simple, implementation is problematic. Second, analytical solutions are difficult to achieve except for very simple models. Third, considerable computational cost is required, especially for three-dimensional movements. The result is that models must be simplified in many cases.

3.5 Electromyography (EMG)

Another approach for examining force sharing among synergistic muscles involves the use of electromyography (EMG) to predict muscle forces [69]. The general theory behind the EMG methodology is that the net moment of force at a given joint can be estimated accurately and reliably if the EMG is suitably processed to reflect the activation of each muscle crossing the joint and if this activation is modulated properly according to the known characteristics of muscle mechanics. The first step involves estimating the activation of an individual muscle using the EMG signal and determining the kinematics of each joint that the muscle crosses. The second step involves the input of this data into a Hill-type muscle model to predict the force of that muscle. The third step combines the predicted forces of each individual muscle with a model that contains the moment arm information and passive structural contributions to predict the net moment of force about that joint. The use of muscle models for EMG-to-force processing was first systematically evaluated by [70]. They developed a Hill-type muscle model used to quantify the contributions of the gastrocnemius and soleus muscles to the total plantar flexion moment of the ankle joint.

The advantages of this method are that it uses a dynamic muscle model, takes advantage of all available information, does not depend on imperfect joint torque calculations via inverse dynamics, and is computationally simple enough to be used in 60 real time [71]. The disadvantages of this technique are that it relies extensively on imperfect EMG signals and the parameter values of the musculoskeletal model [71].

3.6 Artificial Neural Networks

Artificial Neural Networks or Neural networks (NN), which are simplified models of the biological neuron system, is a massively parallel distributed processing system made up of highly interconnected neural computing elements that have the ability to learn and thereby acquire knowledge and make it available for use.

Various learning mechanisms exist to enable the NN acquire knowledge. NN architectures have been classified into various types based on their learning mechanisms and other features. Some classes of NN refer to this learning process as training and the ability to solve a problem using the knowledge acquired as inference.

NNs are simplified imitations of the central nervous system, and obviously therefore, have been motivated by the kind of computing performed by the human brain. The structural constituents of the human brain termed neurons are the entities, which perform computations such as cognition, logical inference, pattern recognition and so on. Hence, the technology, which has been built on a simplified imitation of computing by neurons of a brain, has been termed Artificial Neural Systems (ANS) technology or Artificial Neural Networks (ANN) or simply Neural Networks. In some literature, this technology is also referred to as Connectionist Networks, Neuro Computers, and Parallel Distributed Processors etc. Also neurons are referred to as neurodes, Processing Elements (PEs), and nodes.

A human brain develops with time and this, in common parlance is known as experience. Technically, this involves the 'development' of neurons to adapt themselves to their surrounding environment, thus, rendering the brain plastic in its information processing capability. On the similar lines, the property of plasticity is also discussed with respect to NN architectures. Further, the adaptive capability of a NN is in the face of changing environments. Thus, the stability-plasticity issue is of great importance to NN architectures. This is so since NN systems essentially being learning systems need to preserve the information previously learnt but at the same time, need to be receptive to learning new information. The NN needs to remain 'plastic' to significant or useful information but remain 'stable' when presented with irrelevant information. This is known as stability-plasticity dilemma [72] [73].

3.6.1 Human Brain

The human brain is one of the most complicated things which, on the whole, have been poorly understood. However, the concepts of neurons as the fundamental constituents of the brain, attributed to Ramon Y. Cajal (1911), have made the study of its functioning comparatively easier. Figure 3.1 illustrates the physical structure of the human brain.

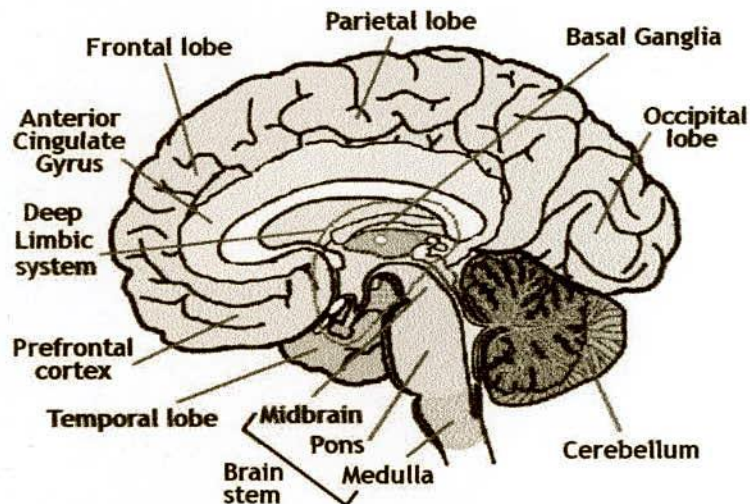


FIGURE 3.1 PHYSICAL STRUCTURE OF THE HUMAN BRAIN- CROSS-SECTIONAL VIEW

Brain contains about 10^{10} basic units called neurons. Each neuron, in turn is connected to another 10^4 other neurons. A neuron is a small cell that receives electro-chemical signals from its various sources and in turn responds by transmitting electrical impulses to other neurons. An average brain weighs about 1.5 kg and an average neuron has a weight of 1.5×10^{-9} grams. While some of the neurons perform input and output, the remaining form a part of an interconnected network of neurons which are responsible for signal transformation and storage of information. However, despite their different activities, all neurons share common characteristics.

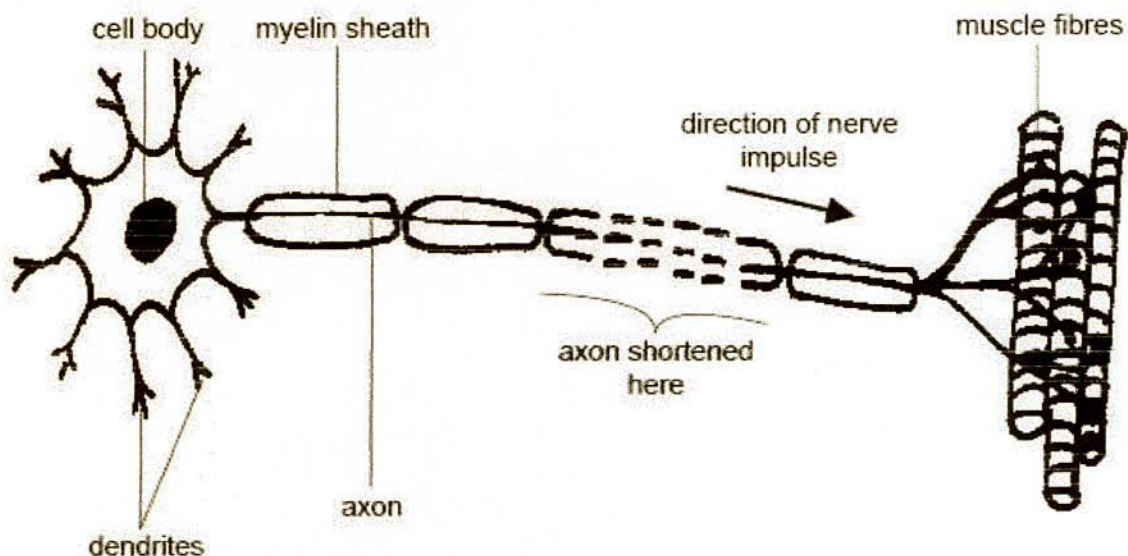


FIGURE 3.2 STRUCTURE OF NEURONS

A neuron is composed of a nucleus- a cell body known as soma (refer Figure. 3.2). Attached to the soma are long irregularly shaped filaments called dendrites. The dendrites behave as input channels, (i.e.) all inputs from other neurons arrive through the dendrites. Dendrites look like branches of a tree during winter. Another type of link attached to the soma is the Axon. Unlike the Dendritic links, the axon is electrically active and serves as an output channel. Axons, which mainly appear as output cells are non-linear threshold devices which produce a voltage pulse called Action Potential or Spike that lasts for about a millisecond. If the cumulative inputs received by the soma raise the internal electric potential of the cell known as Membrane Potential, then the neuron 'fires' by propagating the action potential down the axon to excite or inhibit other neurons. The axon terminates in a specialized contact called synapse or synaptic junction that connects the axon with dendritic links of another neuron. The synaptic junction, which is a very minute gap at the end of the dendritic links contain a neuro-transmitter fluid. It is this fluid which is responsible for accelerating or retarding the electric charges to the soma. Each dendritic link can have many synapses acting on it thus bringing about massive interconnectivity. In general, a single neuron can have many synaptic inputs and synaptic outputs. The size of the synapses is believed to be related to learning. Thus, synapses with larger area are thought to be excitatory while those with smaller area are believed to be inhibitory. Again, it is the increased neuronal activity which is thought to be responsible for learning and memory. In fact, this was what motivated Donald Hebb to suggest "when an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic changes take place in one or both cells such that A's efficiency as one of the cells firing B is increased." These observations branded as Hebbian learning has influenced many learning models in NN over the years. In fact, the neuronal activity can be quite complex but viewing the activity as a simple summation of the inputs they receive, has turned out to be a reasonable approximation.

3.6.2 Model of an Artificial Neuron

The human brain no doubt is a highly complex structure viewed as a massive, highly interconnected network of simple processing elements called neurons. However, the behavior of a neuron can be captured by a simple model as shown in Figure.3.3 Every component of the model bears a direct analogy of the actual constituents of a biological neuron and hence is

termed as artificial neuron. It is the model that forms the basis of the Artificial Neural Networks.

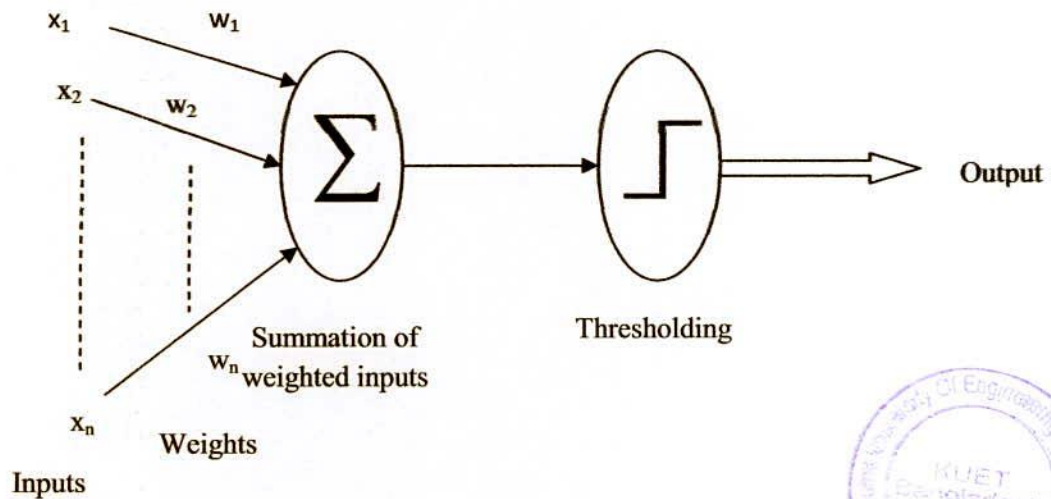


FIGURE 3.3 SIMPLE MODEL OF AN ARTIFICIAL NEURON

Here $x_1, x_2, x_3, \dots, x_n$ are the n inputs to the artificial neuron $w_1, w_2, \dots, w_n$ are the weights attached to the input links.

Recollect that a biological neuron receives all the inputs through the dendrites, sums them and then produces an output if the sum is greater than the threshold value. The input signals are passed on to the cell body through the synapse which may accelerate or retard an arriving signal.

It is the acceleration or retardation of the input signals that is modeled by weights. An effective synapse which transmits a stronger signal will have a correspondingly larger weight while a weak synapse will have smaller weights. Thus, weights here are multiplicative factors of the inputs to account for the strength of the synapse. Hence, the total input I received by the soma of the artificial neuron is

$$\left. \begin{aligned} I &= w_1x_1 + w_2x_2 + \dots + w_nx_n \\ &= \sum_{i=1}^n w_i x_i \end{aligned} \right\} \quad (3.1)$$

To generate the final output y , the sum is passed on to a non-linear filter ϕ called Activation function, or Transfer function, or Squash function which releases the output.

$$y = \phi(I) \quad (3.2)$$

A very commonly used function is the Thresholding function. In this, the sum is compared with a threshold value θ . If the value of I is greater than θ , then the output is 1 else it is 0.

$$y = \phi(\sum w_i x_i - \theta) \quad (3.3)$$

Where, ϕ is the step function known as Heaviside function and is such that

$$\phi(I) = \begin{cases} 1, I > 0 \\ 0, I \leq 0 \end{cases} \quad (3.4)$$

Figure 3.4 illustrates the Thresholding function. This is convenient in the sense that the output signal is either 1 or 0 resulting in the neuron being on or off.

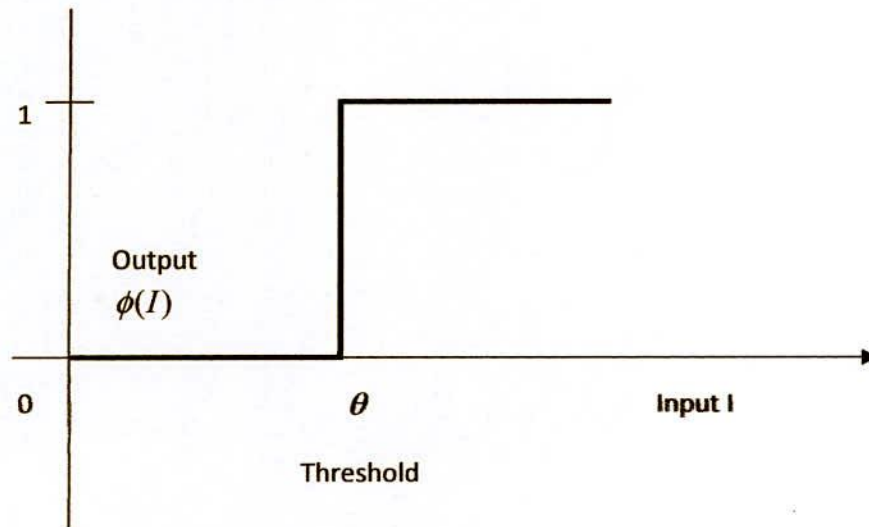


FIGURE 3.4 THRESHOLDING FUNCTION

The other choices for Activation function besides Thresholding function are as given below:

Signum function

Also known as the Quantizer function, the function ϕ is defined as

$$\phi(I) = \begin{cases} +1, I > \theta \\ -1, I \leq \theta \end{cases} \quad (3.5)$$

Figure 3.5 illustrates the Signum function.

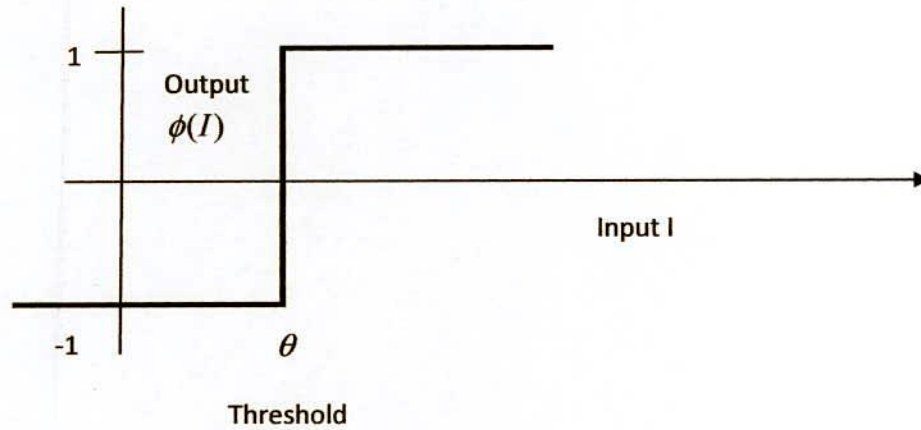


FIGURE 3.5 SIGNUM FUNCTION

Sigmoidal function

This function is a continuous function that varies gradually between the asymptotic values 0 and 1 or -1 and +1 and is given by

$$\phi(I) = \frac{1}{1 + e^{-\alpha I}} \quad (3.6)$$

Where, α is the slope parameter, which adjusts the abruptness of the function as it changes between two asymptotic values. Sigmoidal functions are differentiable, which is an important feature of NN theory.

Hyperbolic tangent function

The function is given by

$$\phi(I) = \tanh(I) \quad (3.7)$$

And can produce negative output values.

The first mathematical model of a biological neuron was presented by McCulloch and Pitts (1943). The model, known as McCulloch-Pitts model does not exhibit any learning but just serves as a basic building block which has inspired further significant work in NN research.

The model makes use of a bias term whose weight is w_0 but with a fixed input of $x_0 = 1$.

This is besides the other inputs x_i and number weights w_i . The bias is an external parameter for the artificial neuron but serves the purpose of increasing or decreasing the net input of the activation function depending on whether it is positive or negative. Other modeling schemes for the neurons have also been proposed. (Macgregor, 1987).

3.6.2.1 Artificial Neural Network Architecture

An artificial network is defined as a data processing system consisting of a large number of simple highly interconnected processing elements (artificial neurons) in an architecture inspired by the structure of the cerebral cortex of the brain (Tsoukalas and Uhrig, 1997). Generally, an ANN structure can be represented using a directed graph. A graph G is an ordered 2-tuple (V, E) consisting of a set V of vertices and a set E of edges. When each edge is assigned an orientation, the graph is directed and is called a directed graph or a diagraph. Figure 3.6 illustrates a diagraph. Diagraphs assume significance in Neural Network theory since signals in NN systems are restricted to flow in specific directions.

The vertices of the graph may represent neurons (input/output) and the edges, the synaptic links. The edges are labeled by the weights attached to the synaptic links.

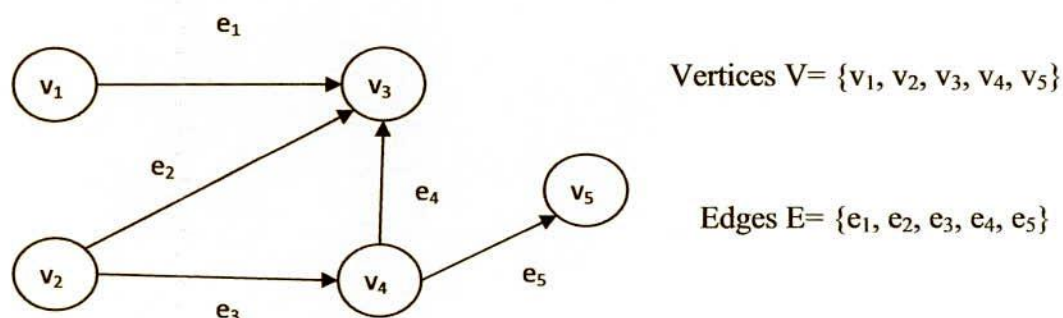


FIGURE 3.6 AN EXAMPLE DIAGRAM OF ANN

There are several classes of NN, classified according to their learning mechanisms. However, we identify three fundamentally different classes of Networks. All the three classes employ the diagraph structure for their representation.

Single Layer Feedforward Network

This type of network comprises of two layers, namely the input layer and the output layer. The input layer neurons receive the input signals, and the output layer neurons receive the

output signals. The synaptic links carrying the weights connect every input neuron to the output neuron but not vice-versa. Such a network is said to be feedforward in type or acyclic in nature. Despite the two layers, the network is termed single layer since it is the output layer, alone which performs computation. The input layer merely transmits the signals to the output layer. Hence, the name single layer feedforward network. The input layer merely transmits the signals to the output layer. Hence the name single layer feedforward network. Figure 3.7 illustrates an example network.

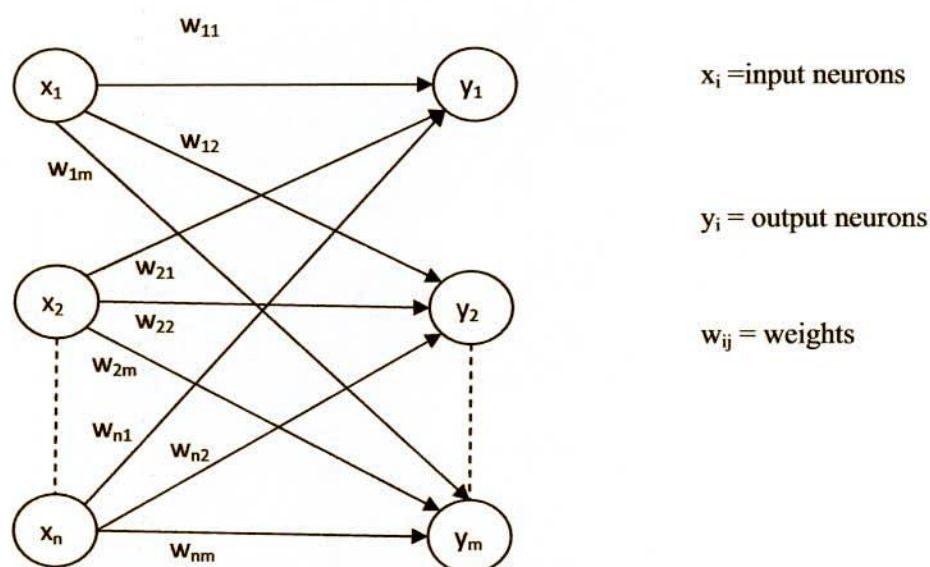


FIGURE 3.7 SINGLE LAYER FEEDFORWARD NETWORK

Multilayer feed forward network

This network, as the name indicates is made up of multiple layers. Thus, architecture of this class besides possessing an input and an output layer also have one or more intermediary layers called hidden layers. The computational units of the hidden layer are known as the hidden neurons or hidden units. The hidden layer aids in performing the useful intermediary computations before directing the input to the output layer. The input layer neurons are linked to the hidden layer neurons and the weights on these links are referred to as input-hidden layer weights. Again, the hidden layer neurons are linked to the output layer neurons and the corresponding weights are referred to as hidden-output layer weights. A multilayer feedforward network with l input neurons, m_1 neurons in the first hidden layer, m_2 neurons in the second hidden layer and n output neurons in the output layer is written as

$l-m_1-m_2-n$. Figure 3.8 illustrates a multilayer feedforward network with a configuration $l-m-n$.

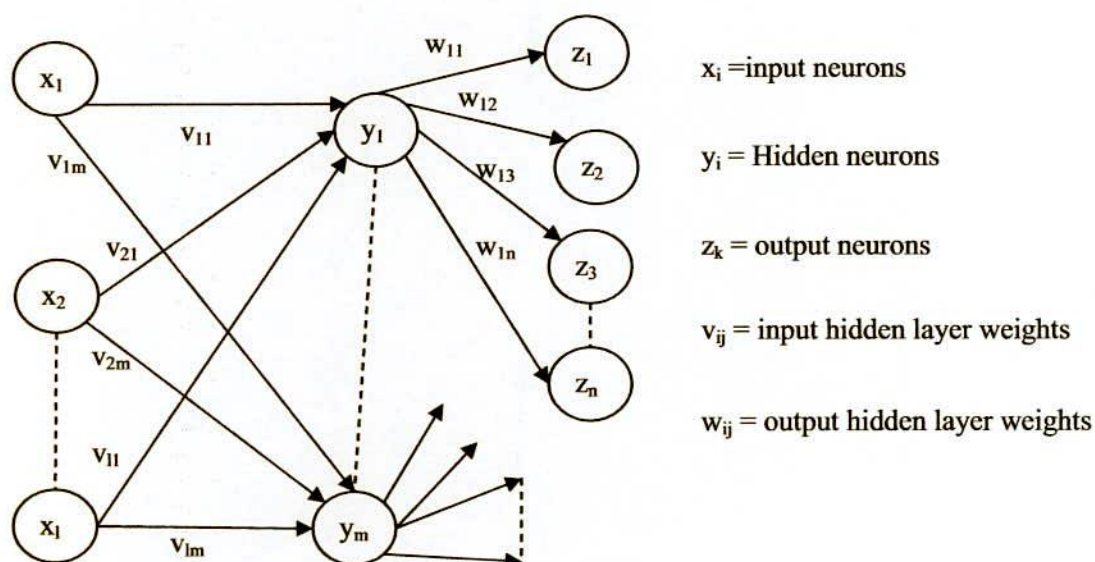


FIGURE 3.8 A MULTILAYER FEEDFORWARD NETWORK (CONFIGURATION)

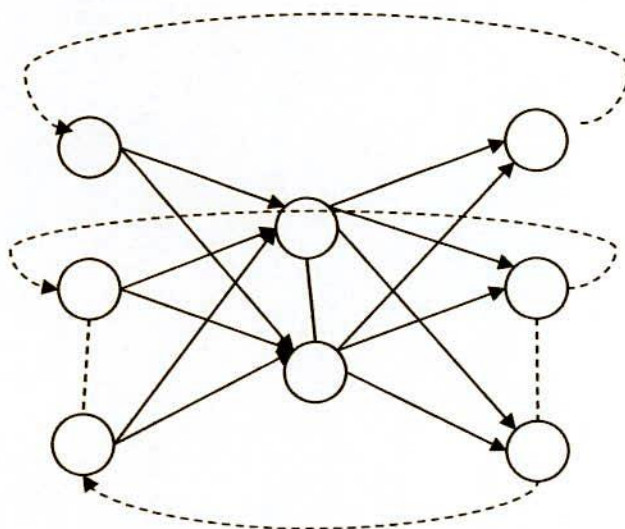


FIGURE 3.9 A RECURRENT NEUTRAL NETWORK

Recurrent Networks

These networks differ from feedforward network architectures in the sense that there is at least one feedback loop. Thus, in these networks, for example, there could exist one layer with feedback connections as shown in Figure 3.9. There could also be neurons with self-feedback links, i.e. the output of a neuron is fed back into itself as input.

3.6.2.2 Characteristics of Neural Networks

- (i) The NNs exhibit mapping capabilities, that is, they can map input patterns to their associated output patterns.
- (ii) The NNs learn by examples. Thus, NN architectures can be 'trained' with known examples of a problem before they are tested for their 'inference' capability on unknown instances of the problem. They can, therefore, identify new objects previously untrained.
- (iii) The NNs possess the capability to generalize. Thus, they can predict new outcomes from past trends.
- (iv) The NNs are robust systems and are fault tolerant. They can, therefore, recall full patterns from incomplete, partial or noisy patterns.
- (v) The NNs can process information in parallel, at high speed, and in a distributed manner.

3.6.2.3 Learning Methods of Neural Networks

Learning methods in Neural Networks can be broadly classified into three basic types: supervised, unsupervised and reinforced.

Supervised learning

In this, every input pattern that is used to train the network is associated with an output pattern, which is the target of the desired pattern. A teacher is assumed to be present during the learning process, when a comparison process is made between the network's computed output and correct expected output, to determine the error. The error can then be used to change network parameters.

Unsupervised learning

In this learning method, the target point is not presented to the network. It is as if there is no teacher to present the desired patterns and hence, the system learns of its own by discovering and adapting to structural features in the input patterns.

Reinforced learning

In this method, a teacher though available, does not present the expected answer but only indicates if the computed output is correct or incorrect. The information provided helps the network in its learning process. A reward is given for a correct answer computed and a penalty for a wrong answer. But, reinforced learning is not one of the popular forms of learning.

3.6.2.4 Artificial Neural Networks Using EMG

Artificial neural networks, has been gaining widespread use to study the force sharing problem (for reviews, see Bullock et al., 1996; Herzog et al., 1999; Koike and Kawato, 2000). Artificial neural networks have successfully been used to predict joint moments and muscle forces in cat locomotion [74], human locomotion [75] and upper limb movements [76].

3.7 Support Vector Machine

The SVM is a very popular algorithm for solving pattern recognition, regression and density estimation problems, and has already outperformed most of the machine learning algorithms. Theoretically, the SVM approximately implements the structural risk minimization principle, thus the SVM is situated on a strong theoretical foundation. The SVM is a linear classifier that maximizes the margin between the separating hyper plane and the training data points. It has no local minima, i.e., it solves a convex optimization problem. The algorithm can automatically determine network architecture. For these reasons, it is much more attractive in application areas than the other neural networks. Basically SVM is designed for binary classification problems, and many different forms of SVM algorithms have been introduced for different purposes. In this section, we describe only the binary SVM classifier (Figure 3.10).

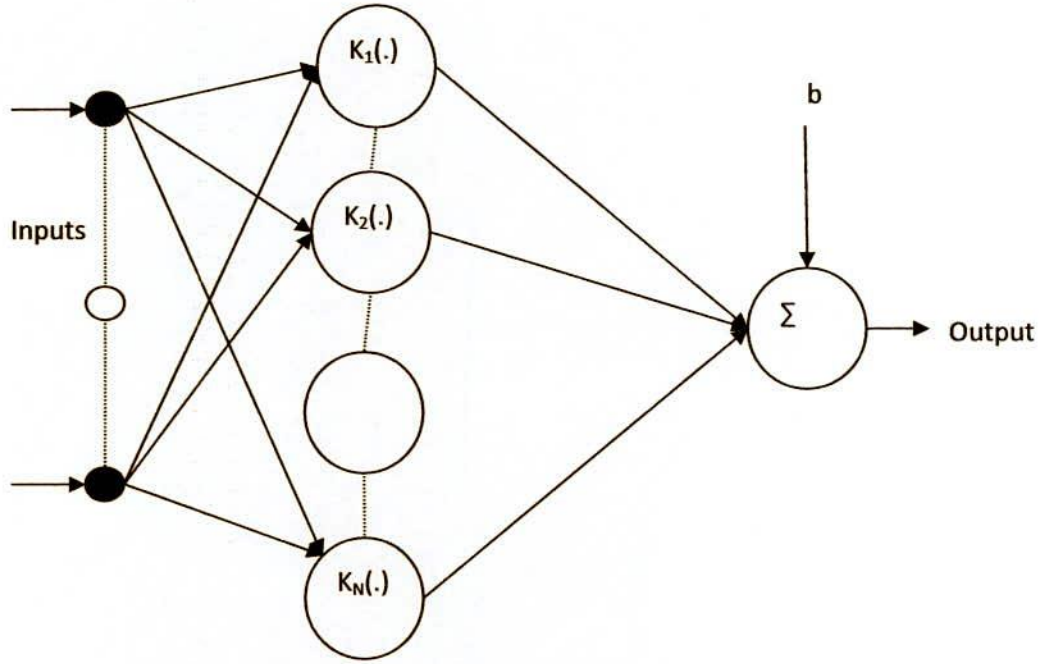


FIGURE 3.10 ARCHITECTURE OF SVM (N NUMBERS OF SUPPORT VECTORS)

The SVM developed by Vapnik et al. [77] has been shown to be a powerful supervised learning tool. The standard soft-margin SVM is a binary classifier applied to classify a data set defined as

$$\Theta = \left\{ \begin{array}{l} (x_1, y_1), (x_2, y_2), \dots, (x_l, y_l) \\ x_i \in \mathbb{R}^n \\ y_i = \{1, -1\} \end{array} \right\} \quad (3.8)$$

Where Θ are vectors containing the measurements of ECG data and y are the corresponding class labels. The SVM formulation is essentially a regularized minimization problem leading to the use of Lagrange Theory and quadratic programming techniques. The formulation defines a boundary separating two classes in the form of a linear hyper plane in data space where the distance between the boundaries of the two classes and the hyper plane is known as the margin of the hyper plane [78]. This idea is further extended for data that is not linearly separable; where it is first mapped via a nonlinear function to a higher dimension feature space. Maximizing the margin of the hyperplane in either space is equivalent to maximizing the distance between the class boundaries. In Figure 3.11, an optimal separating hyperplane is

shown as the one that generates the maximum margin (dashed line) between the two data sets. The separating hyperplane has the following form:

$$f(x) = \sum_{i=1}^l w_i \phi(x_i) + b \quad (3.9)$$

Where w_i the weights of the hyperplane and the scalar b are is the hyperplane bias. In fact, the nonlinear mapping $\phi: x \in \mathbb{R}^n \rightarrow \mathbb{R}^m$ and $n, m \in [1, \infty)$ defines the mapping from data space to feature space. Hence, the weights in feature space will have a one to one correspondence with the elements of $\phi(x)$. Now for separation in feature space; we would like to obtain the hyperplane with the following properties:

$$\left. \begin{aligned} f(x) &= \sum_{i=1}^l w_i \phi(x_i) + b \\ f(x) &> 0 \quad \forall i: y_i = +1 \\ f(x) &< 0 \quad \forall i: y_i = -1 \end{aligned} \right\} \quad (3.10)$$

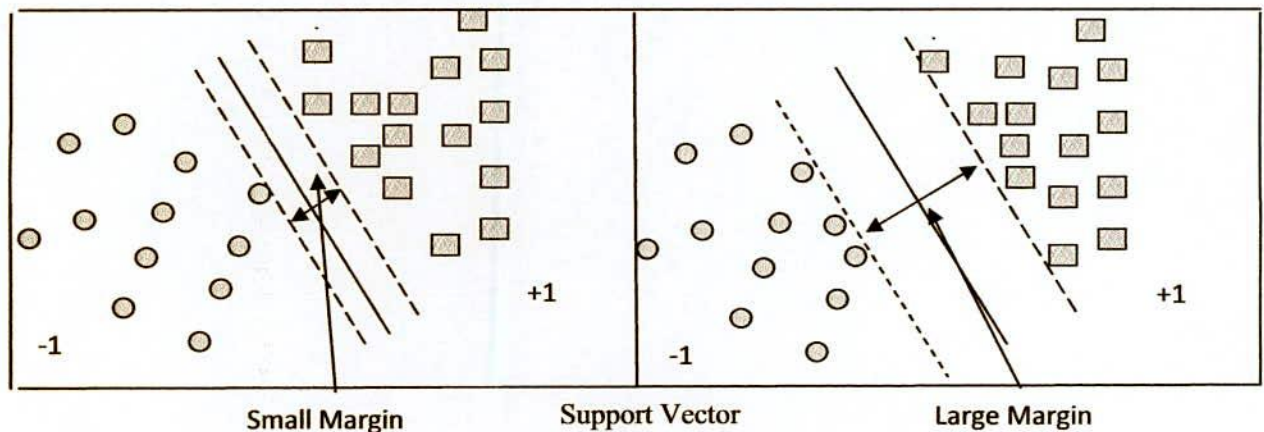


FIGURE 3.11 HYPERLANE USING LINEAR SUPPORT VECTOR MACHINE

The conditions above can be described by a strict linear discriminant function [78], so that for each element pair in Θ , we require that

$$y_i \left(\sum_{i=1}^l w_i \phi(x_i) + b \right) \geq 1. \quad (3.11)$$

The distance from the hyperplane to a support vector is $\frac{1}{\|w\|}$ and the distance between the support vectors of one class to the other class is simply $\frac{2}{\|w\|}$ by geometry. The soft-margin minimization problem relaxes the strict discriminate in (3.11) by introducing slack variables ξ_i , and is formulated as

$$\begin{aligned} \text{minimize } \mathfrak{J}(w, \xi) &= \frac{1}{2} \sum_{i=1}^l w_i^2 + C \sum_{i=1}^l \xi_i \\ \text{subject to } &\begin{cases} y_i \left(\sum_{i=1}^l w_i \phi(x_i) + b \right) \geq 1 + \xi_i \\ \forall i = 1, \dots, l \end{cases} \end{aligned} \quad (3.12)$$

We now apply Lagrange Theory (details can be found in Vapnik [77]) to solve (3.9) giving us the usually solved dual Lagrangian form of

$$\begin{aligned} \text{minimize } \mathfrak{J}(\alpha) &= -\sum_{i=1}^l \alpha_i + \frac{1}{2} \sum_{i,j=1}^l \alpha_i \alpha_j y_i y_j K(x_i, x_j) \\ \text{subject to } &\begin{cases} 0 \leq \alpha_i \leq C \\ \sum_{i=1}^l \alpha_i y_i = 0 \end{cases} \end{aligned} \quad (3.13)$$

Where C is a constant parameter, called regularization parameter, that determines the tradeoff between the maximum margin and minimum classification error [78]. The explicit definition of the nonlinear mapping $\phi(x)$ has been circumvented by the use of the kernel function defined as

$$K(x, y) = \langle \phi(x), \phi(y) \rangle \quad (3.14)$$

The separating hyperplane surface in (3.9) can now be written in terms of Lagrange Multipliers as

$$f(x) = \text{sgn} \left(\sum_{i=1}^l \alpha_i y_i K(x, x_i) + b \right) \quad (3.15)$$

The process of obtaining the quadratic program solution is known as training the SVM and using the trained SVM to classify new examples is known as testing.

3.7.1 SVM Kernel Function

The most common kernel functions are linear, polynomial, Gaussian radial basis function (RBF) and Sigmoid kernel. These kernels have the following forms, respectively.

- 1) Linear $K(x_i, x_j) = x_i \cdot x_j$
- 2) Polynomial: $K(x_i, x_j) = (x_i \cdot x_j + r)^d$, d is the degree of polynomial.
- 3) Gaussian radial basis function (RBF): $K(x_i, x_j) = \exp(-(\|x_i - x_j\|^2)/(2\sigma^2))$, σ is the width of RBF function.
- 4) Sigmoid kernel $K(x_i, x_j) = \tanh(ax_i \cdot x_j + r)$, which takes two parameters: a and r .

For $a > 0$, we can view a as a scaling parameter of the input data, and r as a shifting parameter [79] that controls the threshold of mapping.

3.7.2 Support Vector Regression

Suppose we are given training data $\{(x_1, y_1), \dots, (x_l, y_l)\} \subset X \times \mathbb{R}$, where X denotes the space of the input patterns (e.g. $X = \mathbb{R}^d$). These might be, for instance, SEMG for some subject measured at subsequent time together with corresponding force indicators. In ϵ -SV regression proposed by Vapnik in 1995, our goal is to find a function $f(x)$ that has at most ϵ deviation from the actually obtained targets y_i for all the training data, and at the same time is as flat as possible. In other words, we do not care about errors as long as they are less than ϵ , but will not accept any deviation larger than this. This may be important if we want to be sure not to accept more than ϵ error when dealing with force prediction, for instance. For pedagogical reasons, we begin by describing the case of linear functions f , taking the form

$$f(x) = \langle w, x \rangle + b \text{ with } w \in X, b \in \mathbb{R} \quad (3.16)$$

Where, $\langle \bullet, \bullet \rangle$ denotes the dot product in X . Flatness in the case of (3.16) means that one seeks a small w . One way to ensure this is to minimize the norm, $\|w\|^2 = \langle w, w \rangle$. We can write this problem as a convex optimization problem:

$$\begin{aligned}
& \text{minimize} && \frac{1}{2} \|w\|^2 \\
& \text{subject to} && \begin{cases} y_i - \langle w, x_i \rangle - b \leq \varepsilon \\ \langle w, x_i \rangle + b - y_i \leq \varepsilon \end{cases}
\end{aligned} \tag{3.17}$$

The tacit assumption in (3.17) was that such a function f actually exists that approximates all pairs (x_i, y_i) with ε precision, or in other words, that the convex optimization problem is feasible. Sometimes, however, this may not be the case, or we also may want to allow for some errors. Analogously to the “soft margin” loss function which was adapted to SV machines by Cortes and Vapnik one can introduce slack variables ξ_i, ξ_i^* to cope with otherwise in-feasible constraints of the optimization problem (3.17). Hence we arrive at the formulation started in (3.12).

$$\begin{aligned}
& \text{minimize} && \mathfrak{J}(w, \xi, \xi^*) = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^l (\xi_i + \xi_i^*) \\
& \text{subject to} && \begin{cases} y_i - \langle w, x_i \rangle - b \leq \varepsilon + \xi_i \\ \langle w, x_i \rangle + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i + \xi_i^* \geq 0 \end{cases}
\end{aligned} \tag{3.18}$$

The constant $C > 0$ determines the trade-off between the flatness of f and the amount up to which deviations larger than ε are tolerated. This corresponds to dealing with a so called ε -insensitive loss function $|\xi|_\varepsilon$ described by

$$|\xi|_\varepsilon = \begin{cases} 0 & \text{if } |\xi| \leq \varepsilon \\ |\xi| - \varepsilon & \text{otherwise} \end{cases} \tag{3.19}$$

Figure. 3.12 depicts the situation graphically. Only the points outside the shaded region contribute to the cost insofar, as the deviations are penalized in a linear fashion.

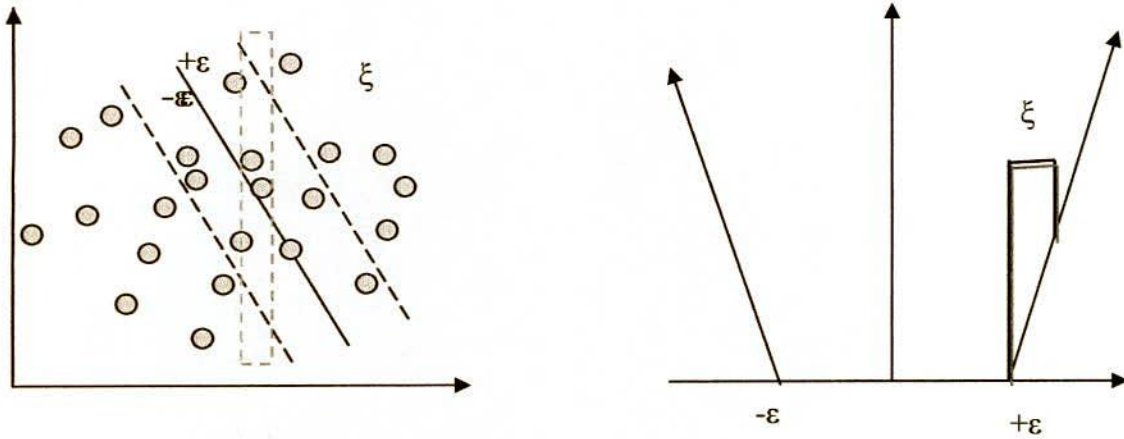


FIGURE 3.12 THE SOFT MARGIN LOSS SETTING FOR A LINEAR SVM

In most cases the optimization problem (3.18) can be solved more easily in its dual formulation. Moreover, as we will see in Sec. 3.9, the dual formulation provides the key for extending SV machine to nonlinear functions.

Dual Problem and Quadratic Programs

The key idea is to construct a Lagrange function from the objective function (it will be called the primal objective function in the rest of this article) and the corresponding constraints by introducing a dual set of variables. It can be shown that this function has a saddle point with respect to the primal and dual variables at the solution. We proceed as follows:

$$L = \begin{cases} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^l (\xi_i + \xi_i^*) - \sum_{i=1}^l (\eta_i \xi_i + \eta_i^* \xi_i^*) \\ - \sum_{i=1}^l \alpha_i (\varepsilon + \xi_i - y_i + \langle w, x_i \rangle + b) \\ - \sum_{i=1}^l \alpha_i^* (\varepsilon + \xi_i^* - y_i + \langle w, x_i \rangle + b) \end{cases} \quad (3.20)$$

Here L is the Lagrangian and η_i , η_i^* , α_i , α_i^* are Lagrange multipliers. Hence the dual variables in (3.20) have to satisfy positivity constraints, i.e.

$$\alpha_i^*, \eta_i^* \geq 0 \quad (3.21)$$

It follows from the saddle point condition that the partial derivatives of L with respect to the primal variables (w, b, ξ_i, ξ_i^*) have to vanish for optimality

$$\frac{\partial L}{\partial b} = \sum_{i=1}^l (\alpha_i^* - \alpha_i) = 0 \quad (3.22)$$

$$\frac{\partial L}{\partial w} = w - \sum_{i=1}^l (\alpha_i - \alpha_i^*) = 0 \quad (3.23)$$

$$\frac{\partial L}{\partial \xi_i^*} = C - \alpha_i^* - \eta_i^* = 0 \quad (3.24)$$

Substituting (3.22), (3.23), and (3.24) into (3.20) yields the dual optimization problem.

$$\begin{aligned} \text{maximize } & \left\{ -\frac{1}{2} \sum_{i,j} (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) \langle x_i, x_j \rangle - \varepsilon \sum_i (\alpha_i + \alpha_i^*) + \sum_i y_i (\alpha_i - \alpha_i^*) \right. \\ & \left. \text{subject to } \sum_i (\alpha_i + \alpha_i^*) \text{ and } \alpha_i, \alpha_i^* \in [0, C] \right\} \end{aligned} \quad (3.25)$$

In deriving (3.25) we already eliminated the dual variables η_i, η_i^* through condition (3.24) which can be reformulated as $\eta_i^* = C - \alpha_i^*$. Eq. (3.23) can be rewritten as follows

$$w = \sum_{i=1}^l (\alpha_i - \alpha_i^*) x_i, \quad \text{thus} \quad f(x) = \sum_{i=1}^l (\alpha_i - \alpha_i^*) \langle x_i, x \rangle + b \quad (3.26)$$

This is the so-called Support Vector expansion, i.e. w can be completely described as a linear combination of the training patterns x_i . In a sense, the complexity of a function's representation by SVs is independent of the dimensionality of the input space X , and depends only on the number of SVs. Moreover, note that the complete algorithm can be described in terms of dot products between the data. Even when evaluating $f(x)$ we need not compute w explicitly. These observations will come in handy for the formulation of a nonlinear extension.

Computing b

So far we neglected the issue of computing b . The latter can be done by exploiting the so called Karush–Kuhn–Tucker (KKT) conditions. These state that at the point of the solution the product between dual variables and constraints has to vanish.

$$\begin{cases} \alpha_i (\varepsilon + \xi_i - y_i + \langle w, x_i \rangle + b) = 0 \\ \alpha_i^* (\varepsilon + \xi_i + y_i - \langle w, x_i \rangle - b) = 0 \end{cases} \quad (3.27)$$

$$\begin{cases} (C - \alpha_i) \xi_i = 0 \\ (C - \alpha_i^*) \xi_i^* = 0 \end{cases} \quad (3.28)$$

This allows us to make several useful conclusions. Firstly only samples (x_i, y_i) with corresponding $\alpha_i^* = C$ lie outside the ε -insensitive tube. Secondly $\alpha_i \alpha_i^* = 0$, i.e. there can never be a set of dual variables α_i, α_i^* which are both simultaneously nonzero. This allows us to conclude that

$$\varepsilon - y_i + \langle w, x_i \rangle + b \geq 0 \text{ and } \xi_i = 0 \text{ if } \alpha_i < C \quad (3.29)$$

$$\varepsilon - y_i + \langle w, x_i \rangle + b \leq 0 \quad \text{if } \alpha_i < 0 \quad (3.30)$$

In conjunction with an analogous analysis on α_i^* we have

$$\begin{aligned} \max \{ -\varepsilon + y_i - \langle w, x_i \rangle \mid \alpha_i < C \text{ or } \alpha_i^* > 0 \} &\leq b \leq \\ \min \{ -\varepsilon + y_i - \langle w, x_i \rangle \mid \alpha_i > 0 \text{ or } \alpha_i^* < 0 \} &\end{aligned} \quad (3.31)$$

CHAPTER 4

Experimental Procedures and Setup

4.1 Necessary tools

There are different types of tool and software required for data acquisition from subjects some important tools are listed in table 4.1 it should be remember that we used other basic tools like personal computers, adapter, voltage regulator, connecting cable, chair, table etc. Details about the item 1 to 6 of the table 4.1 can be found in [80].

TABLE 4.1 TOOLS REACQUIRED FOR DATA ACQUISITION

	Name of the tool	Model	Description	Used for
1.	Hand Dynamometer	SS25LA (BIOPAC)	• Nominal Output 35 μv/Kg • Weight 0.323 Kg • Dimensions: 17.78 cm X 5.59 cm X 2.54 cm (Lxwxh)	Collecting clench strength
2.	Cable (SEMG)	BSL-SS2LB	• Fully shielded • Permits high- resolution recording	Recording of biopotentials (SEMG)
3.	Cable	SS25LA	• Fully shielded • Permits high- resolution recording	Recording of force data
4.	Vinyl Electrodes	EL503	• Disposable	Connecting the body with data acquisition cable
5.	Data Acquisition Hardware	BIOPAC MP36	• Built-in universal amplifiers	Recording and conditioning electrical signals

				from the muscle and hand dianamometer
6.	Gel	BIOPAC gel 101	Formulated with 0.5% saline in a neutral base	Ensuring better conductivity between muscle and the electrode.

4.2 Experimental Setup

Figure 4.1 illustrate the experimental setup, which is used for both SEMG and clench strength data collection simultaneously. BIOPAC Hand Dynamometer used to collect clench strength. Fully shielded BSL-SS2LB cable assembly permits high-resolution recording of biopotentials (SEMG) using disposable vinyl electrodes (EL503). BIOPAC MP36 data acquisition hardware used to record and condition electrical signals from the muscle via BSL-SS2LB (channel 3) force data using SS25LA (channel 1).



FIGURE 4.1 EXPERIMENTAL SETUP FOR DATA ACQUISITION

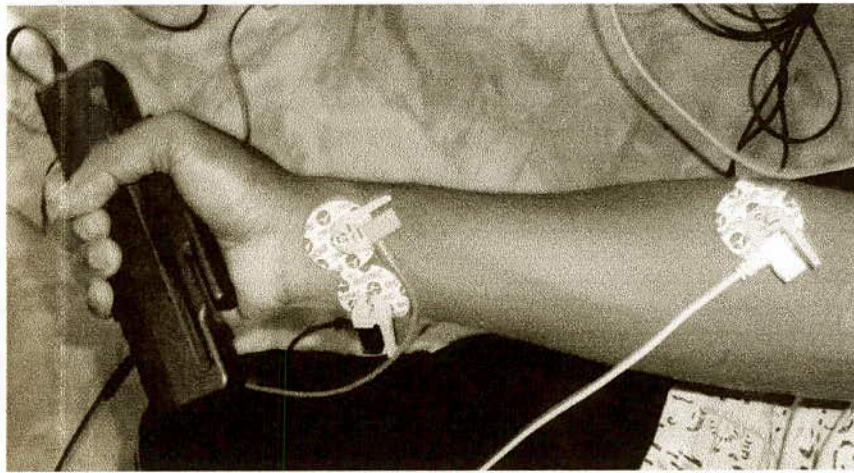


FIGURE 4.2 ELECTRODE PLACEMENT FOR DATA ACQUISITION

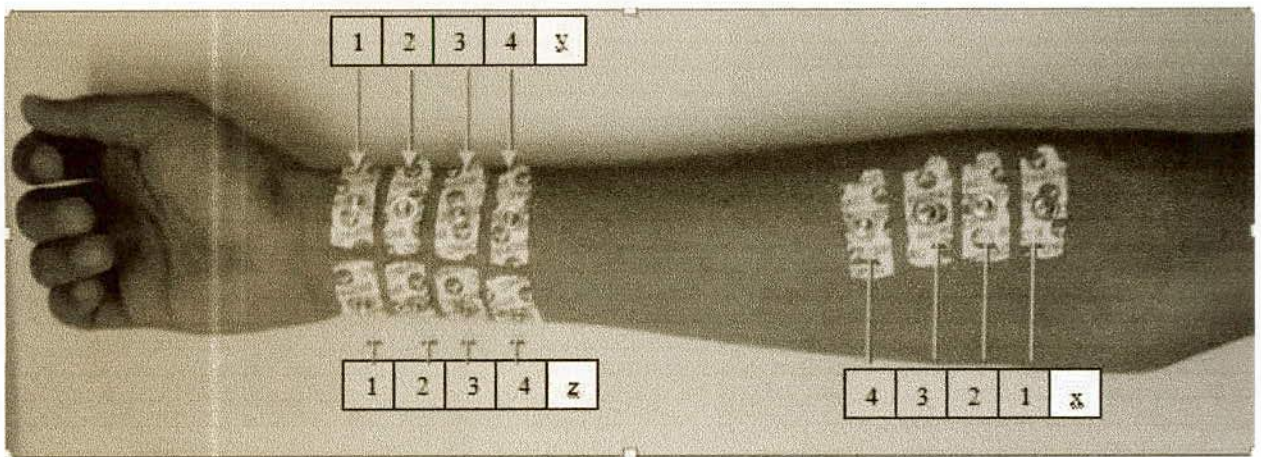


FIGURE 4.3 ELECTRODE PLACEMENT FOR LEAD DISPLACEMENT DATA ACQUISITION

The subjects were requested to sit comfortably on an armed chair and their forearms were positioned on an arm of the chair (Figure 4.1). A force dynamometer was placed between subject's thumb finger and another finger having 6 cm apart as shown in Figure 4.2. Figure 4.3 shows the electrodes combination for the experiment done to see the effect of lead displacement. Here three electrodes position are marked with x, y and z and these positions have four individual position marked as 1, 2, 3 and 4 which creates total 64 combinations.

4.3 Data Acquisition

Five volunteers with a mean age of 23.4 years take part in our experiment and they were acknowledged about the risk associated with the experiments. The relatively narrow age range was chosen to minimize the effect of age, which is described [81]. All subject reported no

history of upper extremity or other musculoskeletal compliments. Details about the subjects are showed in table 4.2.

TABLE 4.2 INFORMATION OF THE SUBJECTS

	Subject	Age	Height	Weight	Sex	Dominant forearm	History of musculoskeletal compliments
1.	S1	22	5'6"	60	M	Right	No
2.	S2	24	5'6.5"	65	M	Right	No
3.	S3	25	5'7"	56	M	Right	No
4.	S4	25	5'5"	62	M	Right	No
5.	S5	21	6'	60	M	Right	No

The subjects were asked to fully relax their forearm muscles to avoid any other forces except the clench force. All the subjects were instructed to produce the clench force prior to the experiment. Before the experiment the skin were cleaned by dried clean cloth. We only shaved one subject arm because other subjects had only tinny and thin hairs on their arm that did not significantly hinder the conductivity of the SEMG measurements. We used BIOPAC gel 101, formulated with 0.5% saline in a neutral base to ensure better conductivity between muscle and the electrode. Three SEMG electrodes were placed above the center of the muscle using no adhesive tape (Figure 4.2).

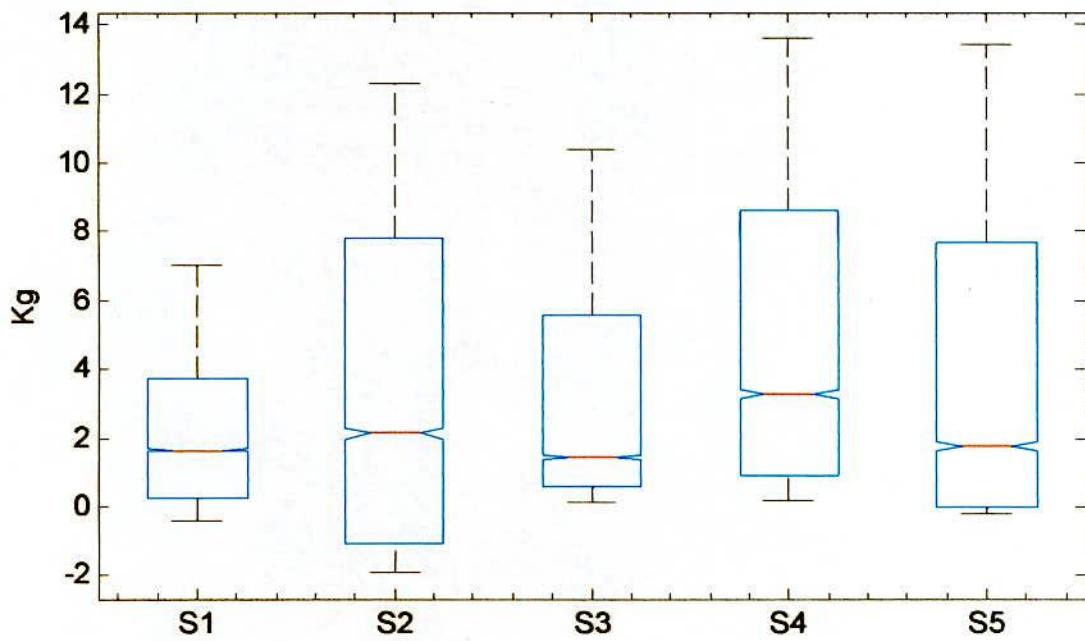


FIGURE 4.4 FORCE RECORDED USING HAND DYNAMOMETER FROM FIVE DIFFERENT SUBJECTS (S1, S2, S3, S4, S5)

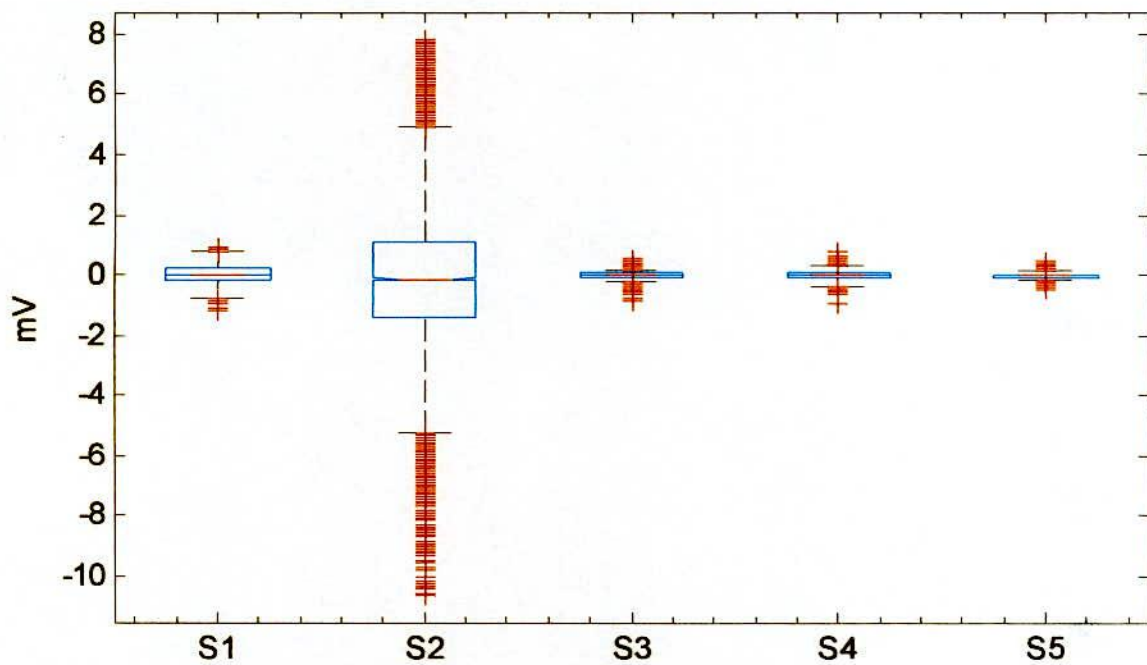


FIGURE 4.5 SEMG DATA FROM FIVE DIFFERENT SUBJECTS (S1, S2, S3, S4, S5)

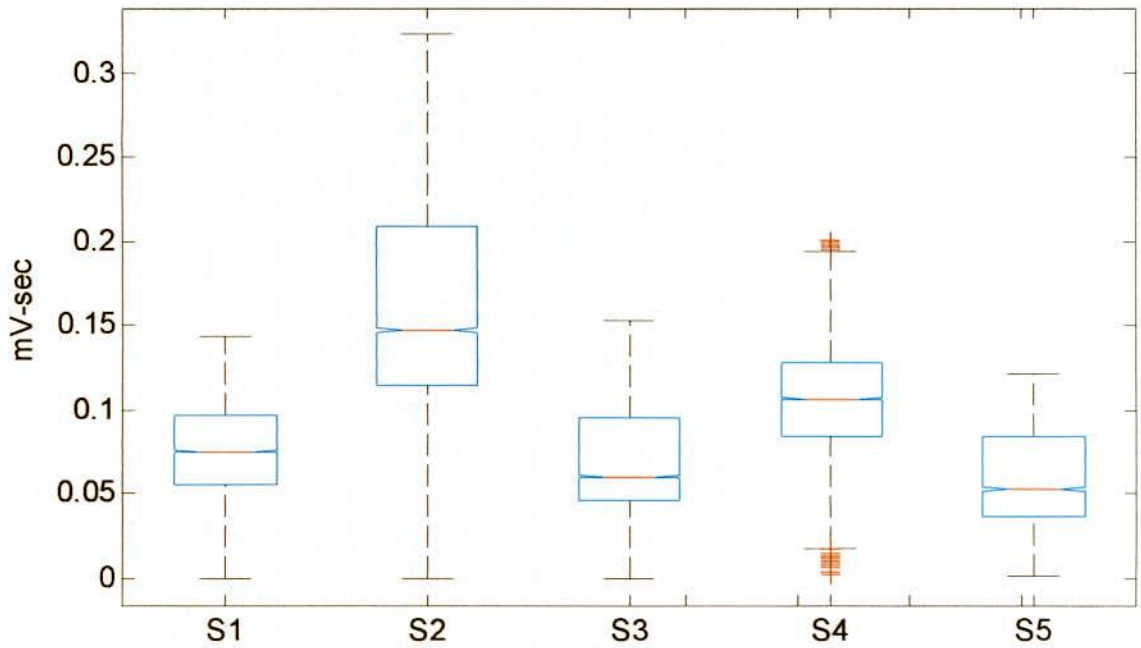


FIGURE 4.6 INTEGRATED SEMG DATA FROM FIVE DIFFERENT SUBJECTS (S1, S2, S3, S4, S5)

The experiment consisted of five trials from five subjects (S1, S2, S3, S4, and S5). The subjects were asked to generate dynamic force and SEMG were simultaneously recorded using the experimental setup. For better understanding the sufficient information from the recorded data, data are presented in box whisker plot instead of time scale plotting. The minimum value and maximum value are represented by “whiskers”; median value is the red line in the box and the box itself represent 50 percent of the force data (Figure 4.4), SEMG (Figure 4.5) and Integrated SEMG (Figure 4.6).

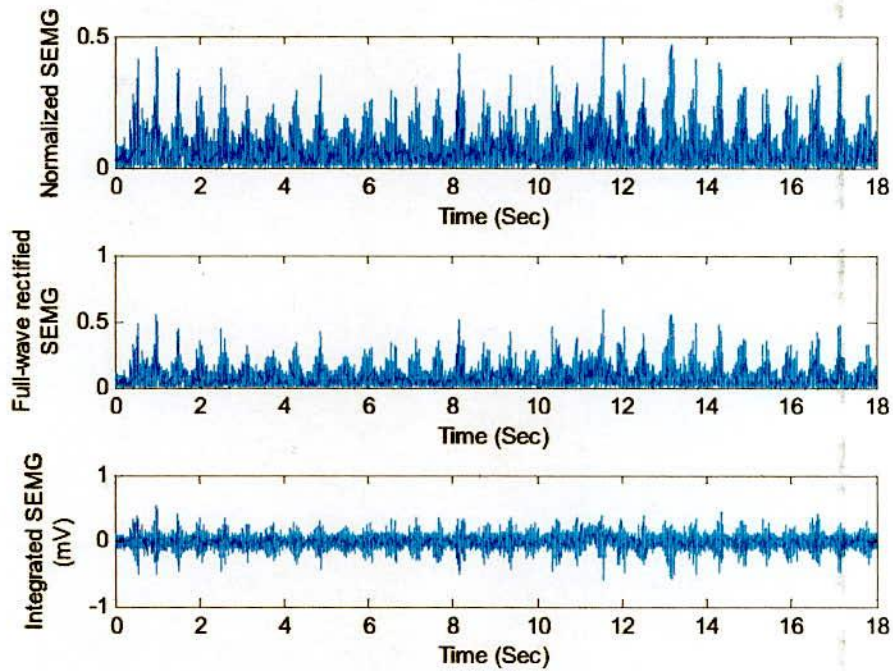
4.4 Pre-processing

The SEMG and force data were first normalized before using as an input for the ANN network. Let the data is $X = \{x_1, x_2, \dots, x_n\}$ where n is the number of data point. From our experience we saw that sometime the output of NN are saturated in one that's why we use x_s to solve the saturation problem. Then the normalized data is given by

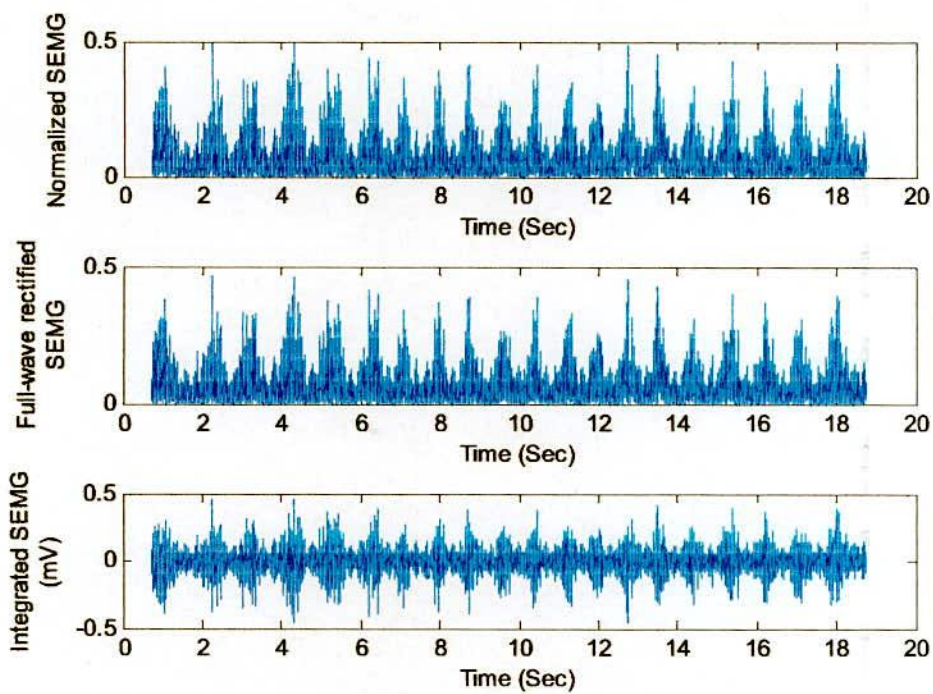
$$x_k = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \times x_s \quad (4.1)$$

Here, $i = k = 1, 2, 3, n$, $x_{\min}$ = minimum value of X

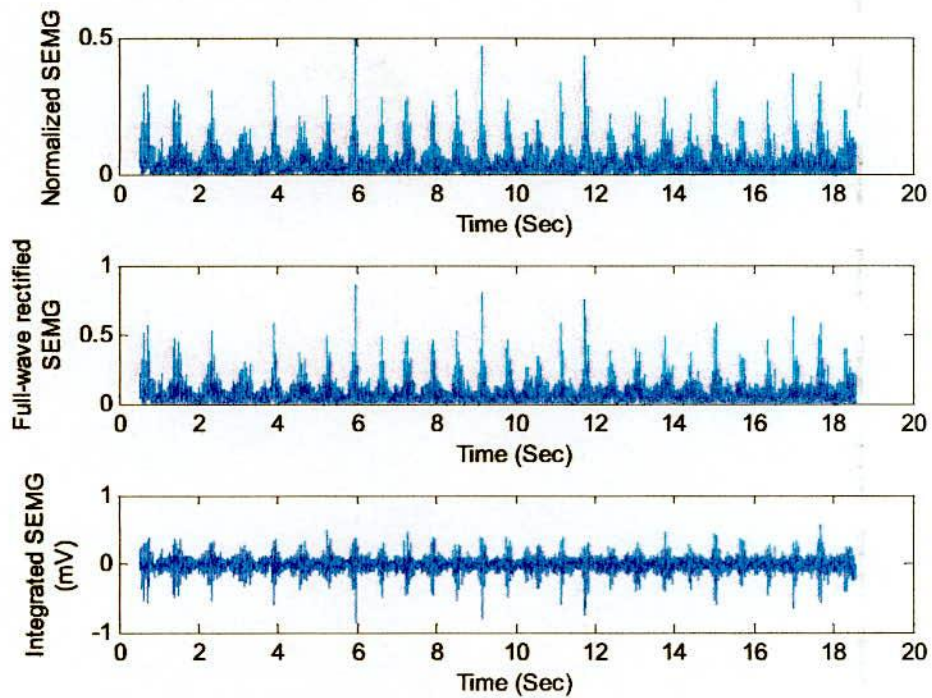
x_{max} = maximum value of X , x_s = scaling factor (0.5 is used)



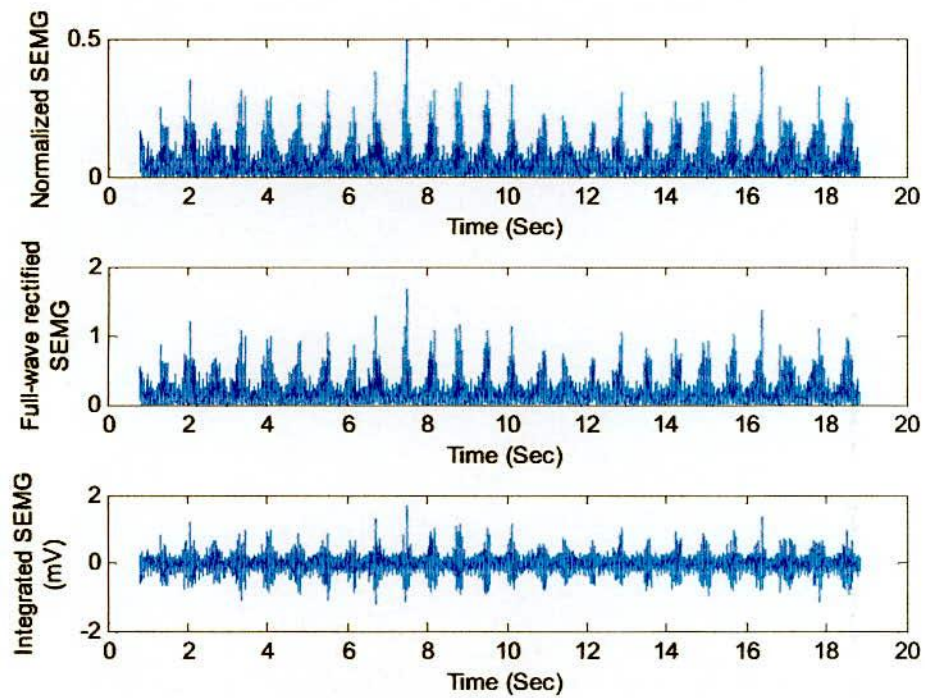
(a) For Subject S1



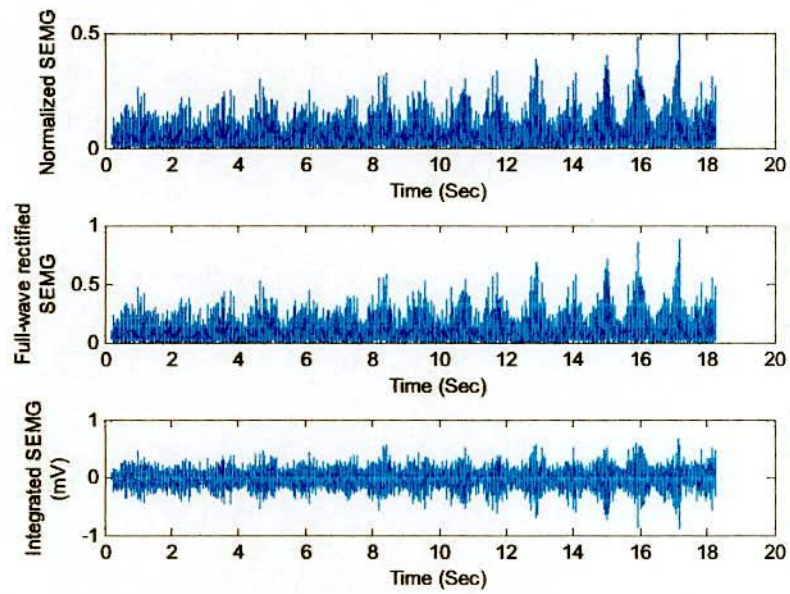
(b) For subject S2



(c) For subject S3

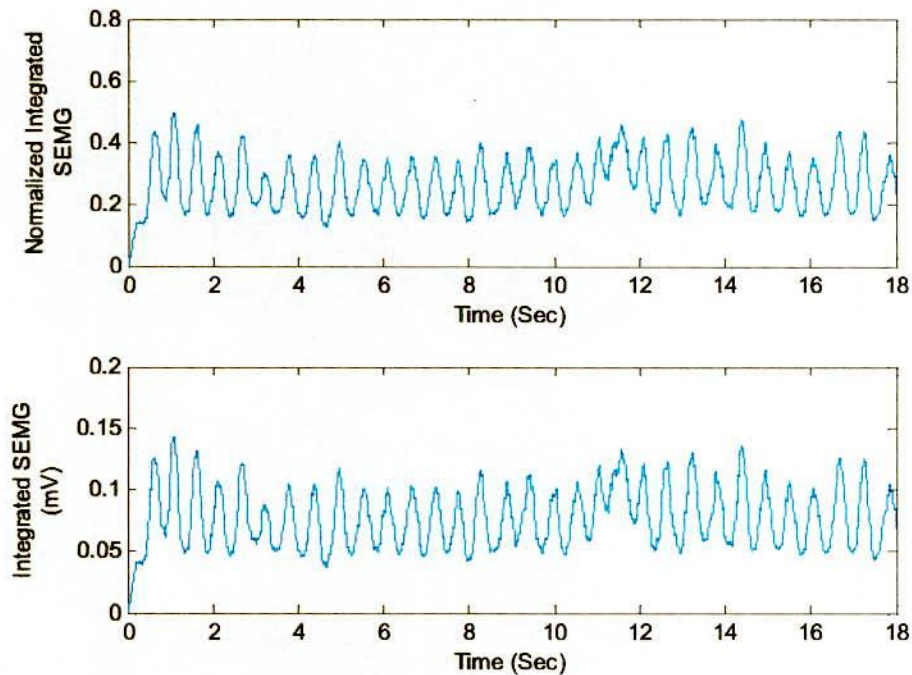


(d) For subject S4

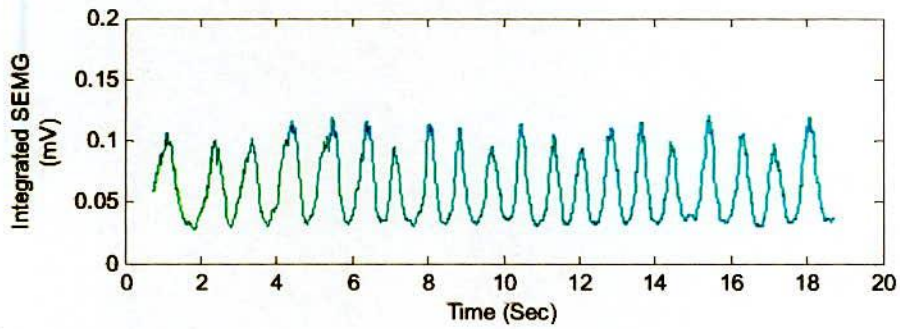
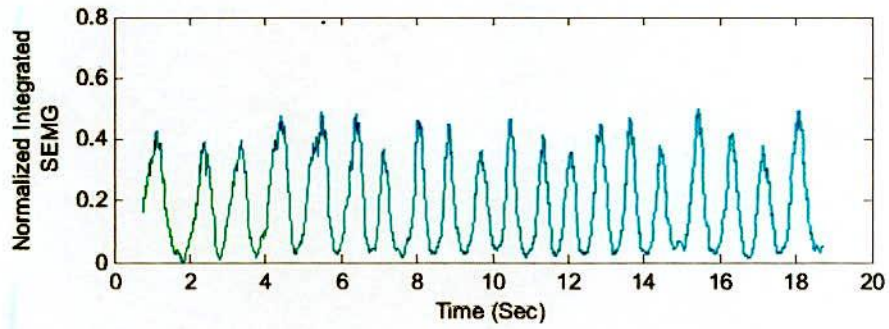


(c) For subject S5

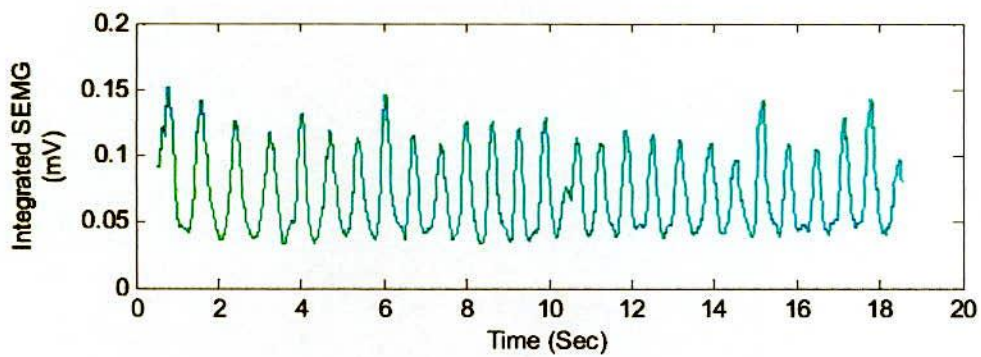
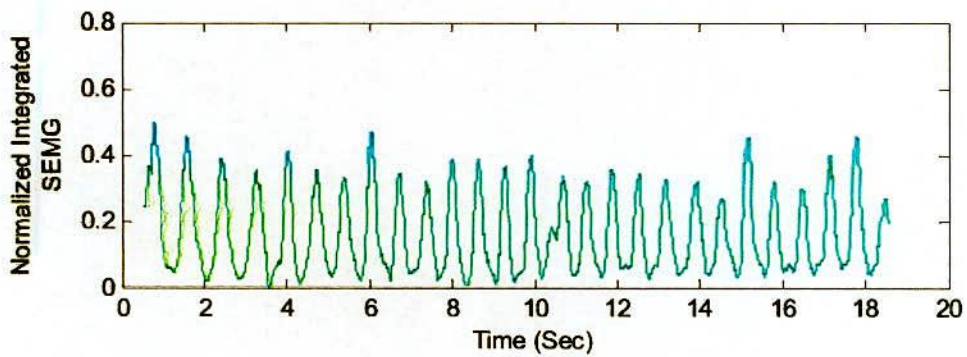
FIGURE 4.7 PRE-PROCESSING OF RAW SEMG FOR THE FEEDING TO THE ANN. ONLY RAW SEMG IS FULL WAVE RECTIFIED BEFORE NORMALIZING



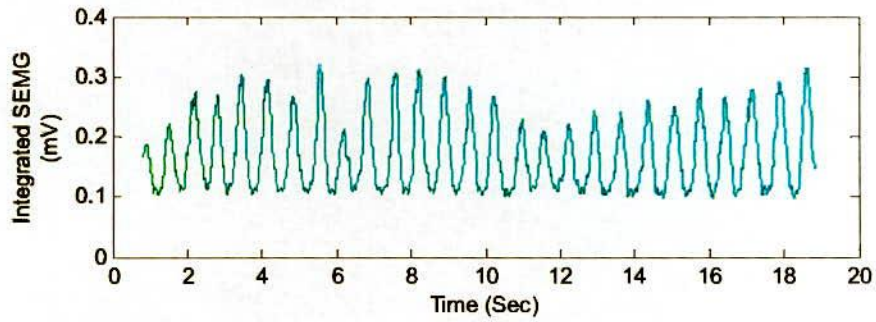
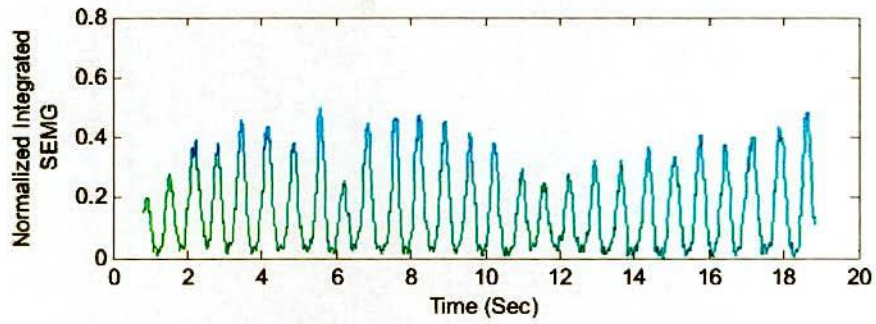
(a) For Subject S1



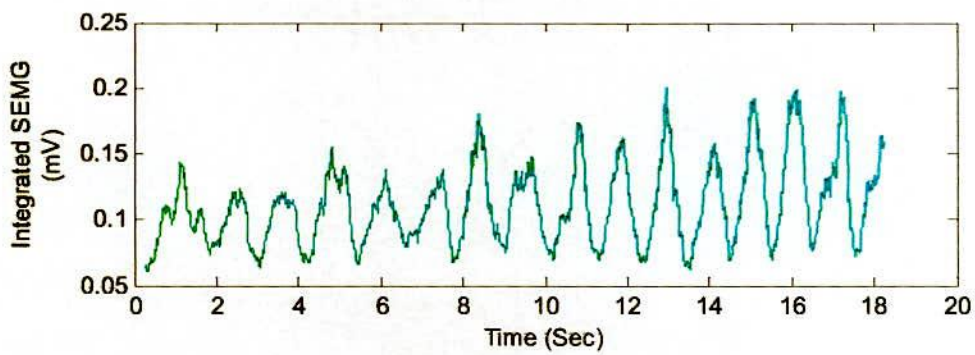
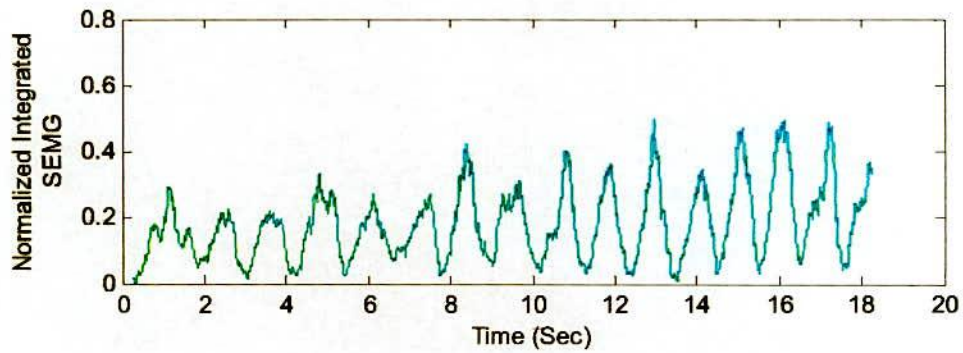
(b) For subject S2



(c) For subject S3

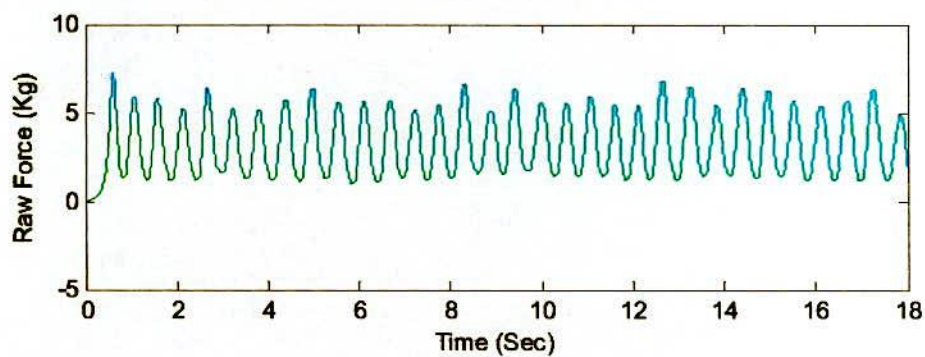
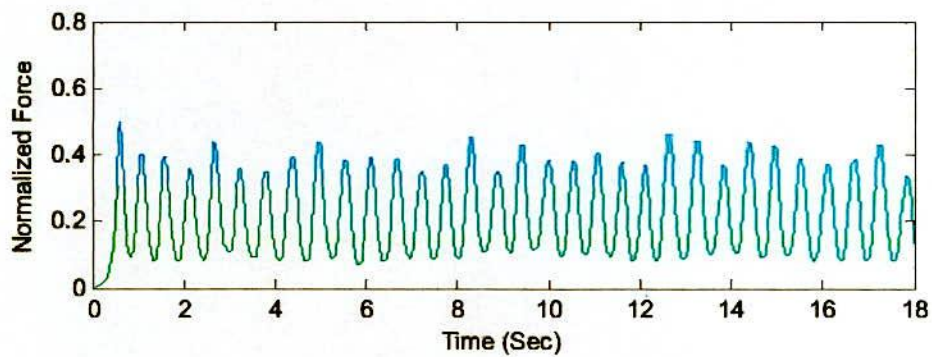


(d) For subject S4

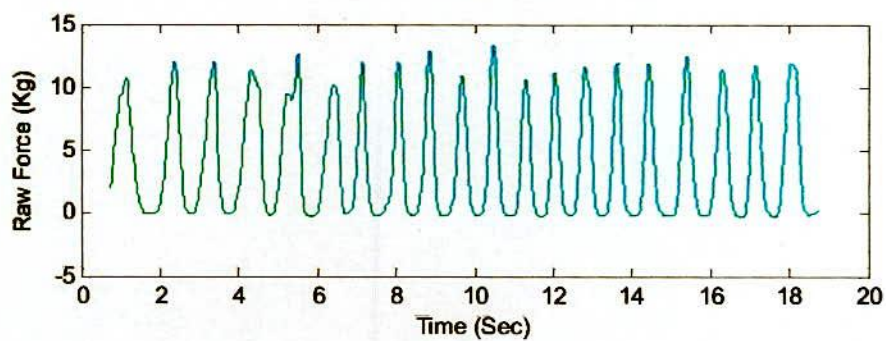
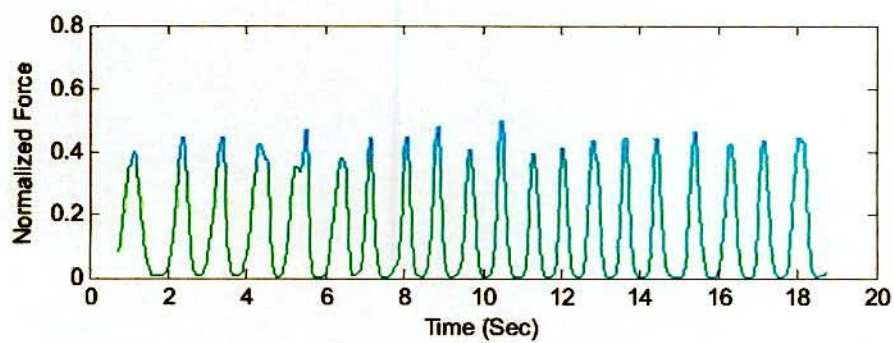


(e) For subject S5

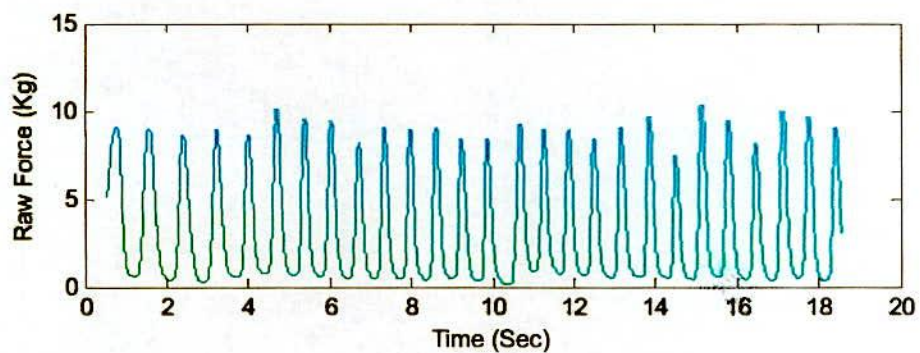
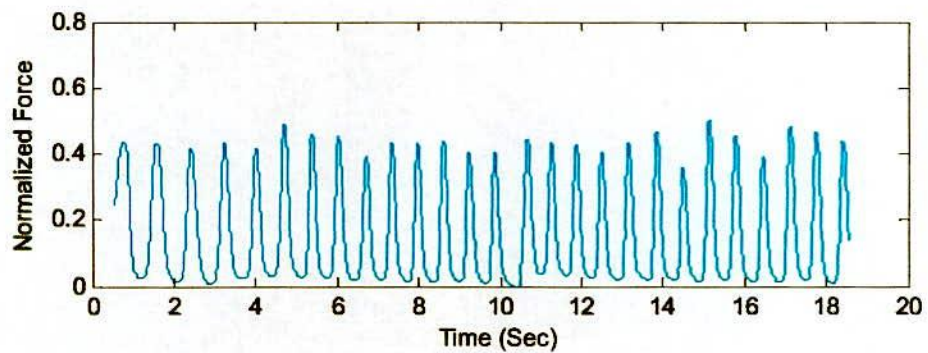
FIGURE 4.8 PRE-PROCESSING OF INTEGRATED SEMG FOR THE FEEDING TO THE ANN



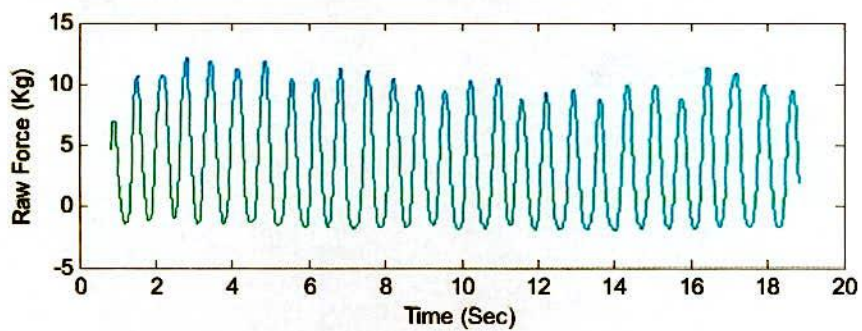
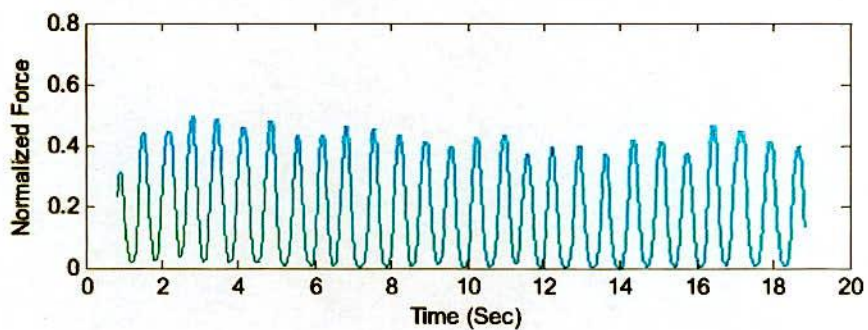
(a) For Subject S1



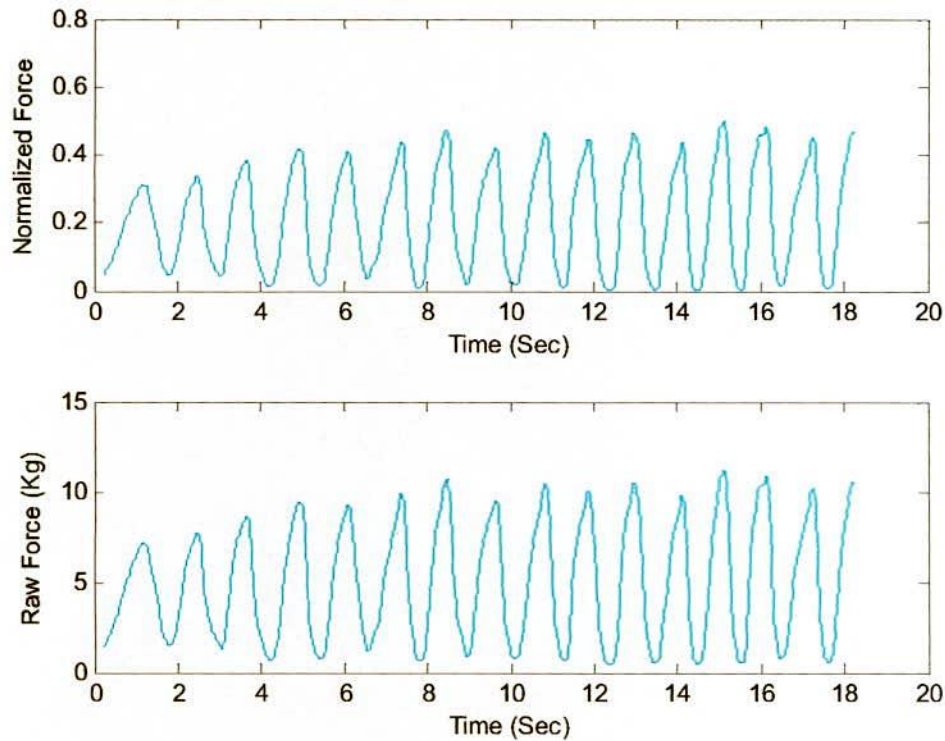
(b) For subject S2



(c) For subject S3



(d) For subject S4



(c) For subject S5

Figure 4.9 PRE-PROCESSING OF FORCE FOR THE FEEDING TO THE ANN

Figure 4.7 shows the preprocessing steps of raw SMEG. In this figure, the lowest row shows the original or raw SMEG, middle row shows the full wave rectified output and the upper row shows the normalized SEMG. The normalized values are used for feeding the ANN. Figure 4.8 shows the integrated SEMG and its normalized value. Similarly, Figure 4.9 shows the preprocessing of clench force.

4.5 ANN structure

In this research, estimator uses the supervised learning method. Here SEMG is used as input to the network. This is associated with an output force that is the target (Figure 4.10). The estimator network consists of a hidden layer is created by using hyperbolic tangent sigmoid transfer function. Output layer uses normal linear transfer. The weights in the estimator are adjusted using Levenberg-Marquardt (L-M) algorithm.

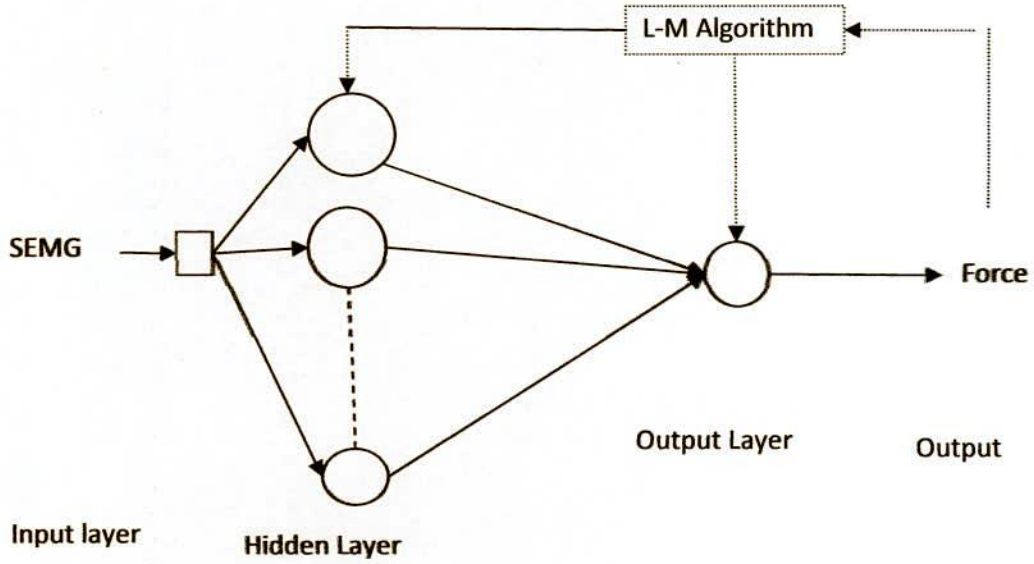


FIGURE 4.10 THE FORCE ESTIMATOR (ANN) USING SEMG

Hidden Layer: According to [82] function signal appearing at the output of neuron j is computed as

$$y_j(n) = \phi(v_j(n)) \quad (4.2)$$

Where, $\phi(\cdot)$ is activation function and $v_j(n)$ is induced local field of neuron j , and is defined by (4.3).

$$v_j(n) = \sum_{i=0}^m w_{ji}(n) y_i(n) \quad (4.3)$$

Where m is the local number of inputs applied to neuron j and w_{ji} is synaptic weight connecting neuron i to neuron j , and $y_i(n)$ is the input signal of neuron j or equivalently the functional signal appearing at output neuron i . If neuron j is the first hidden layer of network, $m = m_0$ and the index i refers to the index i^{th} input terminal of the network, for which we write

$$y_i(n) = x_i(n) \quad (4.4)$$

Where, $x_i(n)$ is i^{th} element of the input vector. A Sigmoid nonlinearity is the hyperbolic tangent function, which is the most general form, and is defined by (4.5)

$$\varphi_j(v_j(n)) = a \tanh(bv_j(n)), \quad (a, b) > 0 \quad (4.5)$$

Here, a and b are the constants. Actually hyperbolic tangent function is the logistic function rescaled and bias

$$\left. \begin{aligned} \varphi'_j(v_j(n)) &= ab \operatorname{sech}^2(bv_j(n)) \\ &= ab(1 - \tanh^2(bv_j(n))) \\ &= \frac{b}{a}[a - y_i(n)][a + y_i(n)] \end{aligned} \right\} \quad (4.6)$$

For a neuron j in a hidden layer, the local gradient is

$$\left. \begin{aligned} \delta_j(n) &= \varphi'_j(v_j(n)) \sum_k \delta_k(n) w_{kj}(n) \\ &= \frac{b}{a}[a - y_i(n)][a + y_i(n)] \sum_k \delta_k(n) w_{kj}(n) \end{aligned} \right\} \quad (4.7)$$

Output Layer: In output layer, the linear neuron uses a linear transfer function.

$$O = g \times I \quad (4.8)$$

Where I is the value coming out of a neuron in the hidden layer is multiplied by a weight associated with the neuron and passed to the summation that adds up the weighted values and presents this sum as the output of the network [83].

The weights were adjusting Levenberg-Marquardt algorithm can be presented as

$$\left. \begin{aligned} w &= w + \Delta w \\ \Delta w &= [J^T J + \eta I]^{-1} J^T e \\ e &= R - z \end{aligned} \right\} \quad (4.9)$$

where, w is the weight vector, Δw is the difference between the weights vectors, J is the Jacobian matrix that contains the first derivative of the networks errors with respect to the weights, η is the scale parameter, I is the identity matrix, R is the reference motion, z is the vector of the estimated motion and e is a vector of network errors [84].

4.6 Procedure to use LIBSVM software [85].

Build libsvm

In libsvm, there exist *svmtrain.exe*, *svmscale.exe*, *svmpredict.exe*, and *svmtoy.exe*.

Using SVM

Libsvm has lots of functions. Here only explains the easier parts (mostly classification with default model).

The programs

We are going to describe how to use the most important executables here in windows platform.

Svmtrain.exe

Use the data for training. But svmtrain accepts some specifically format which will be explained below and then generate a 'Model' file. One may think of a 'Model' as a storage format for the internal data of SVM. This should appear very reasonable after some thought, since training with data is a time-consuming process, so we 'train' first and store the result enabling the 'predict' operation to go much faster.

Svmpredict.exe

Output the predicted class of the new input data according to a pre-trained model.

Svmscale.exe

Rescale data. The original data maybe too huge or small in range, thus we can rescale them to the proper range so that training and predicting will be faster.

File Format of libsvm

This is the input file format of SVM.

```
[label] [index1]:[value1] [index2]:[value2] ...  
[label] [index1]:[value1] [index2]:[value2] ...  
.  
.
```

One record per line, as:

+1 1:0.708 2:1 3:1 4:-0.320 5:-0.105 6:-1

Label

Sometimes referred to as 'class', the class (or set) of our classification. Usually we put integers here.

Index

Ordered indexes are usually continuous integers.

Value

The data for training usually lots of real (floating point) numbers.

Each line has the structure described above. It means, I have an array (vector) of data (numbers): value1, value2, valueN (and the order of the values are specified by the respective index), and the class (or the result) of this array is label.

Maybe it's confusing to you: why value, value2, ...? The reason is usually the input data to the problem we were trying to solve involves lots of 'features', or say 'attributes', so the input will be a set (or say vector/array). Take the Marking points and find region example described above, we assumed each point has coordinates X and Y so it has two attributes (X and Y). To describe two points (0, 3) and (5, 8) as having labels (classes) 1 and 2, we will write them as:

1 1:0 2:3

2 1:5 2:8

and 3-dimensional points will have 3 attributes.

This kind of file format has the advantage that we can specify a sparse matrix, *i.e.* some attribute of a record can be omitted.

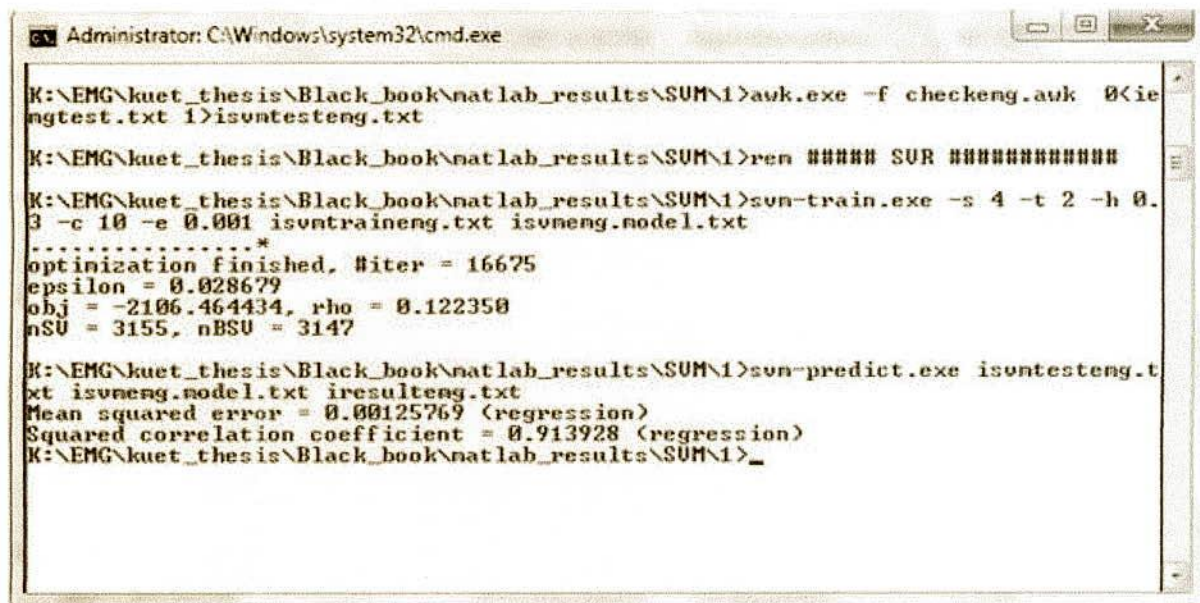
To Run libsvm

You should have a sense that using libsvm is basically:

1. Prepare data in specified format and svmscale it if necessary.
2. Train the data to create a model with svmtrain.

3. Predict new input data with svmpredict and get the result.

After preparing the specified format of libsvm and scaling, use the command prompt and go to the directory where executable file such as svmtrain.exe, svmtrain.exe, svmtrain.exe exist. Then run the svmtrain.exe and svmtrain.exe. The total procedure is given for RBF kernel function starting from the beginning of command prompt as an example.



```
Administrator: C:\Windows\system32\cmd.exe

K:\EMG\kuet_thesis\Black_book\natlab_results\SUM\1>awk.exe -f checkeng.awk 0<ie
mgtest.txt 1>isvntesteng.txt

K:\EMG\kuet_thesis\Black_book\natlab_results\SUM\1>ren ##### SUR #####

K:\EMG\kuet_thesis\Black_book\natlab_results\SUM\1>svm-train.exe -s 4 -t 2 -h 0.
3 -c 10 -e 0.001 isvnttraineng.txt isvnmeng.model.txt
*****
optimization finished, #iter = 16675
epsilon = 0.028679
obj = -2106.464434, rho = 0.122350
nSV = 3155, nBSV = 3147

K:\EMG\kuet_thesis\Black_book\natlab_results\SUM\1>svm-predict.exe isvntesteng.t
xt isvnmeng.model.txt iresulteng.txt
Mean squared error = 0.00125769 (regression)
Squared correlation coefficient = 0.913928 (regression)
K:\EMG\kuet_thesis\Black_book\natlab_results\SUM\1>_
```

FIGURE 4.11 PROCEDURE TO USE LIBSVM IN THE WINDOWS COMMAND PROMPT

svm-train' Usage

Examples of options: -s 0 -c 10 -t 1 -g 1 -r 1 -d 3

Classify a binary data with polynomial kernel $(u \cdot v + 1)^3$ and $C = 10$

Usage: svm-train [options] training_set_file [model file]

Options:

-s svm_type: set type of SVM (default 0)

0 -- C-SVC

1 -- nu-SVC

2 -- one-class SVM

3 -- epsilon-SVR

4 -- nu-SVR



-t kernel type: set type of kernel function (default 2)

0 -- linear: $u \cdot v$

1 -- Polynomial: $(\gamma u \cdot v + \text{coef0})^{\text{degree}}$

2 -- Radial basis function: $\exp(-\gamma |u-v|^2)$

3 -- Sigmoid: $\tanh(\gamma u \cdot v + \text{coef0})$

4 -- Recomputed kernel (kernel values in training_set_file)

-d degree: set degree in kernel function (default 3)

-g gamma: set gamma in kernel function (default $1/\text{num_features}$)

-r coef0: set coef0 in kernel function (default 0)

-c cost: set the parameter C of C-SVC, epsilon-SVR, and nu-SVR (default 1)

-n nu: set the parameter nu of nu-SVC, one-class SVM, and nu-SVR (default 0.5)

-p epsilon: set the epsilon in loss function of epsilon-SVR (default 0.1)

-m cache size: set cache memory size in MB (default 100)

-e epsilon: set tolerance of termination criterion (default 0.001)

-h shrinking: whether to use the shrinking heuristics, 0 or 1 (default 1)

-b probability estimates: whether to train a SVC or SVR model for probability estimates, 0 or 1 (default 0)

-wi weight: set the parameter C of class i to $\text{weight} \cdot C$, for C-SVC (default 1)

-v n: n-fold cross validation mode

-q : quiet mode (no outputs)

The k in the -g option means the number of attributes in the input data.

4.7 Performance Evaluation

Mean Square Error (MSE)

If $F(n)$ is the recorded force signal and $F_m(n)$ be the force signal generated by the model, then Mean Square Error (MSE) is defined as

$$MSE = \frac{1}{N} \sum_{n=0}^{N-1} [F(n) - F_m(n)]^2 \quad (4.10)$$

Mean or Average

$$\mu = \frac{1}{N} \sum_{n=0}^{N-1} [X_m] \quad (4.11)$$

Where, X_m the m^{th} value of the given data.

Standard deviation

$$\sigma_2 = \frac{1}{N} \sum_{n=0}^{N-1} [X_m - \mu]^2 \quad (4.12)$$

In statistics and probability theory, standard deviation (represented by the symbol sigma, σ) shows how much variation or "dispersion" exists from the average (mean, or expected value). A low standard deviation indicates that the data points tend to be very close to the mean, whereas high standard deviation indicates that the data points are spread out over a large range of values.

Cross-Correlation Coefficient (CORR)

Where, N is the total number of input points. An alternative measure of the performance can be evaluated by correlation between estimated force signal, $F_m(n)$ and the original force signal, $F(n)$. The cross-correlation coefficient (CORR) ρ between $F(n)$ and $F_m(n)$ is given by

$$\rho = \frac{\langle [F(n) - \mu_F][F_m(n) - \mu_{F_m}] \rangle}{\sigma_F \sigma_{F_m}} \quad (4.13)$$

Where μ_F and σ_F are the mean and standard deviation of $F(n)$, and μ_{F_m} and σ_{F_m} are the mean and standard deviation of $F_m(n)$. A value of $\rho \sim 1$ reflects a strong correlation, $\rho \sim -1$ implies a strong anticorrelation, and $\rho \sim 0$ indicates that $F(n)$ and $F_m(n)$ are uncorrelated. This means that a value if $\rho = 1$ suggests that technique has successfully estimate force from the SEMG signal.

CHAPTER 5

Results and Discussions

5.1 Database

For evaluating our system a database of five subjects is created. Details data acquisition procedure is discussed in Sec. 4.2. and the summary of the database is

Number of Subjects : 5

Electrode Position : One basic position fault tolerance testing another 63 position.

Example: 123 (means x lead is in 3rd position shown in Figure 4.3 with a displacement of 100% compared with their own size; y position lead displacement is 50% and z positioned lead is its desired position with 0% displacement)

Data : 9000/subject/electrode position.

Average age of subject : 23.4 years

Subjects' sex : Male

Dominate forearm : Right

Time of recording : 18 seconds

History of : No

musculoskeletal
compliments

Example of recorded data is shown in APPENDIX I. Moreover, APPENDIX II shows the sample agreement form or data acquisition sheet which is used in data acquisition procedure.

5.2 Result and Discussion

The main purpose of this paper is to estimate the force. To estimate the force, this total experimental data were divided into three sections. (i) 70% data (6300 data point) were reserve for training purpose (ii) 15% data (1350 data point) for validation and (iii) 15% data (1350 data point) were for testing. These data were randomly selected. The estimator uses feed-forward neural network. The weights of the network were estimated by using L-M

algorithms. After Training, performance of our proposed method was evaluated using MSE and cross-correlation coefficient of (4.12), (4.13) respectively. At first the optimal number of hidden neurons which is 5 is found Figure 5.1 and Figure 5.2.

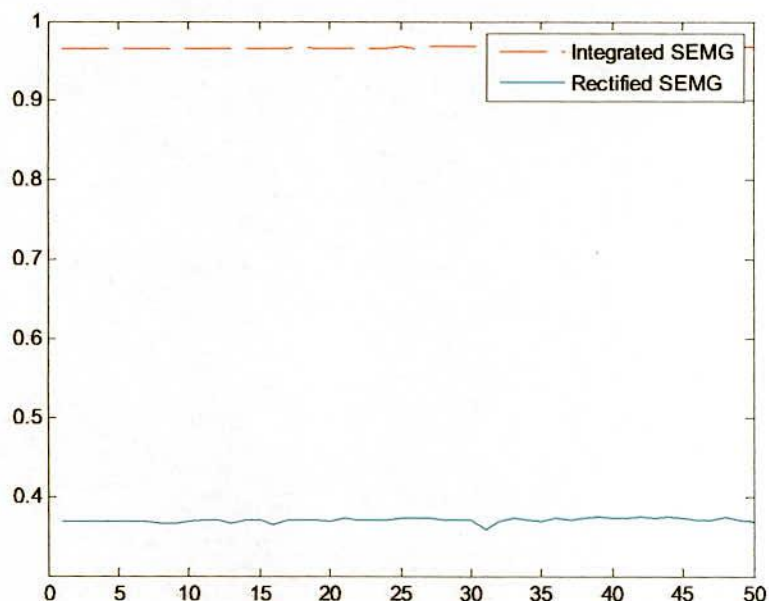


FIGURE 5.1 CROSS-CORRELATION RECTIFIED AND INTEGRATED SEMG OVER DIFFERENT NUMBERS OF HIDDEN NEURONS FOR SUBJECT S2

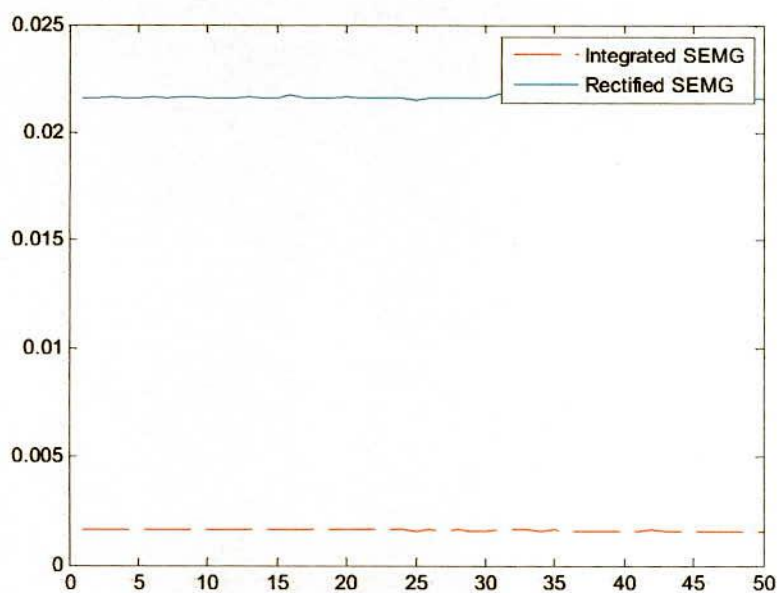
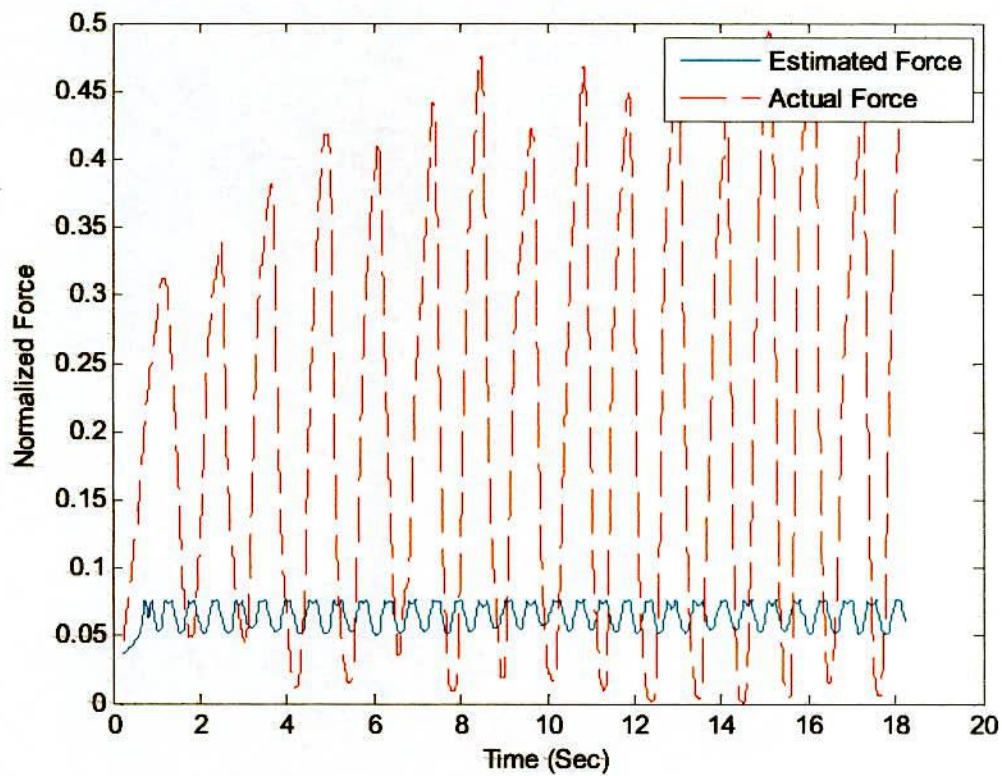
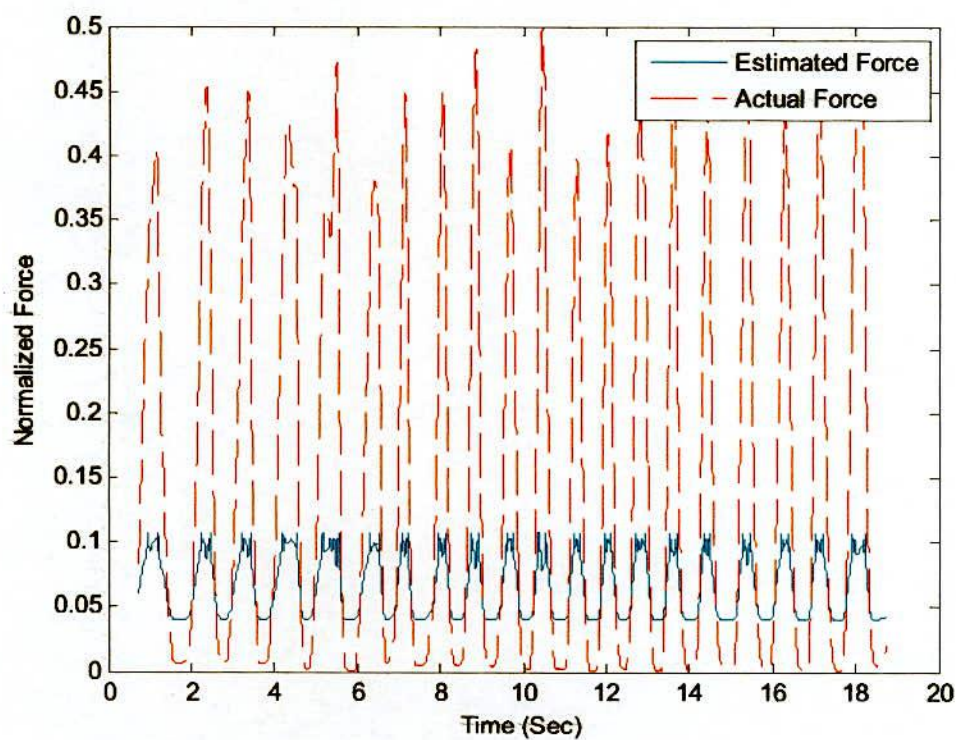


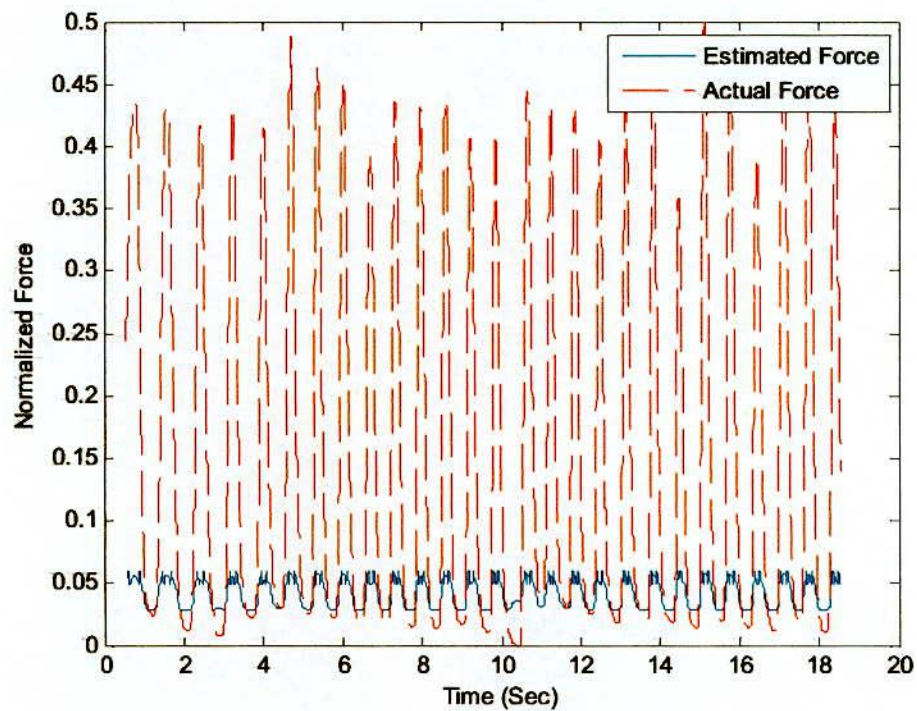
FIGURE 5.2 MSC OF RECTIFIED AND INTEGRATED SEMG OVER DIFFERENT NUMBERS OF HIDDEN NEURONS FOR SUBJECT S2



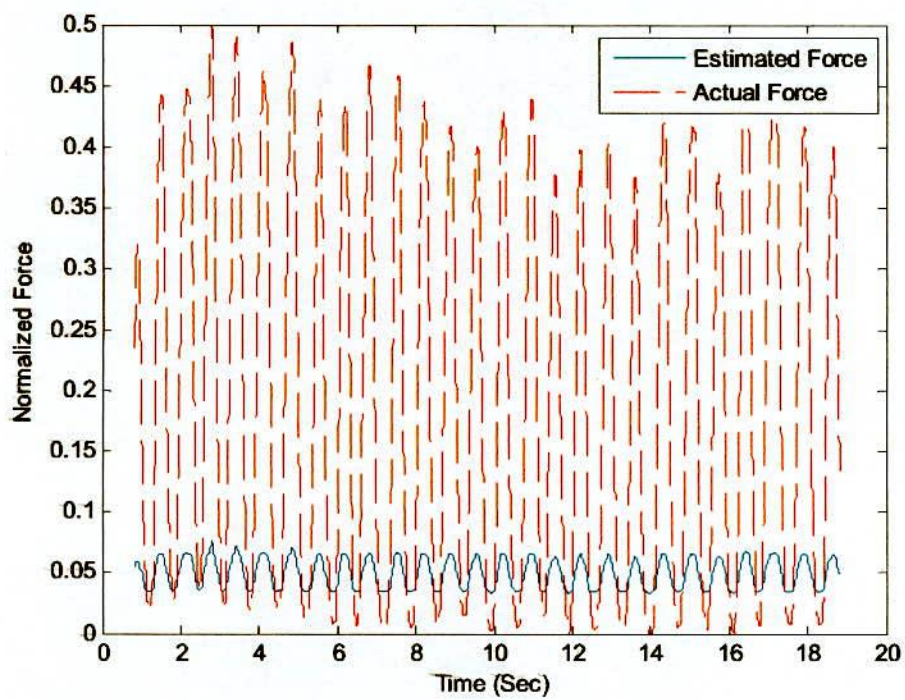
(a) For subject S1



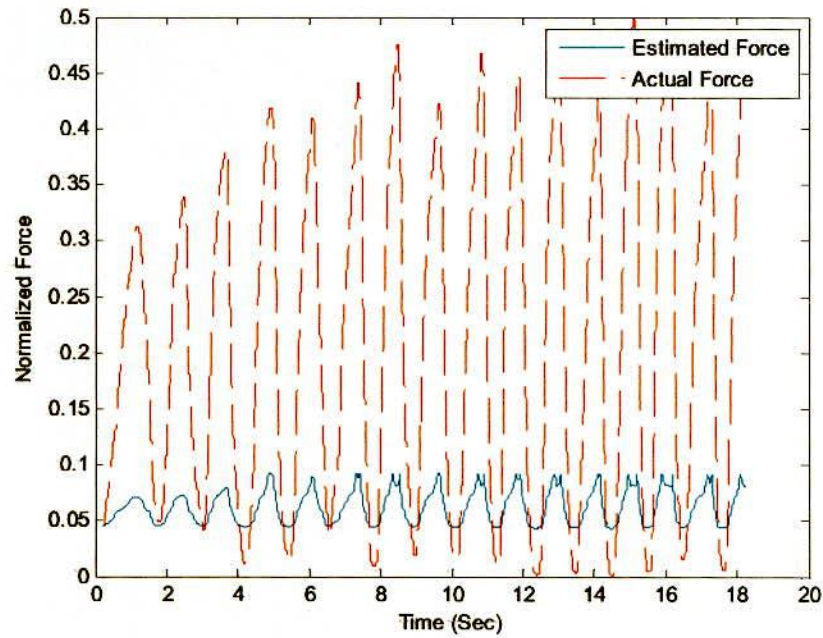
(b) For subject S2



(c) For subject S3

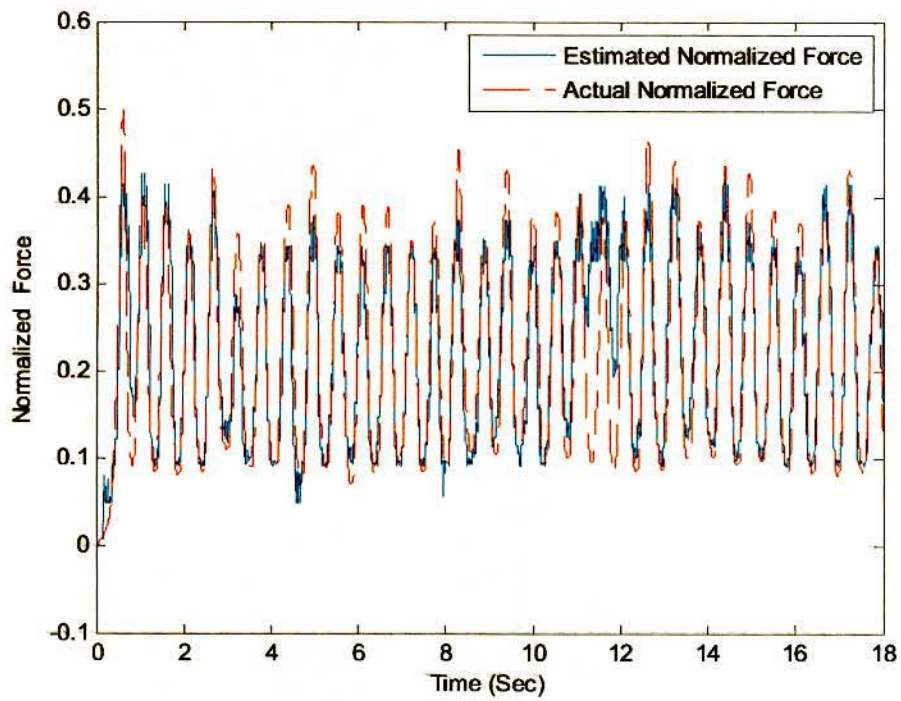


(d) For subject S4

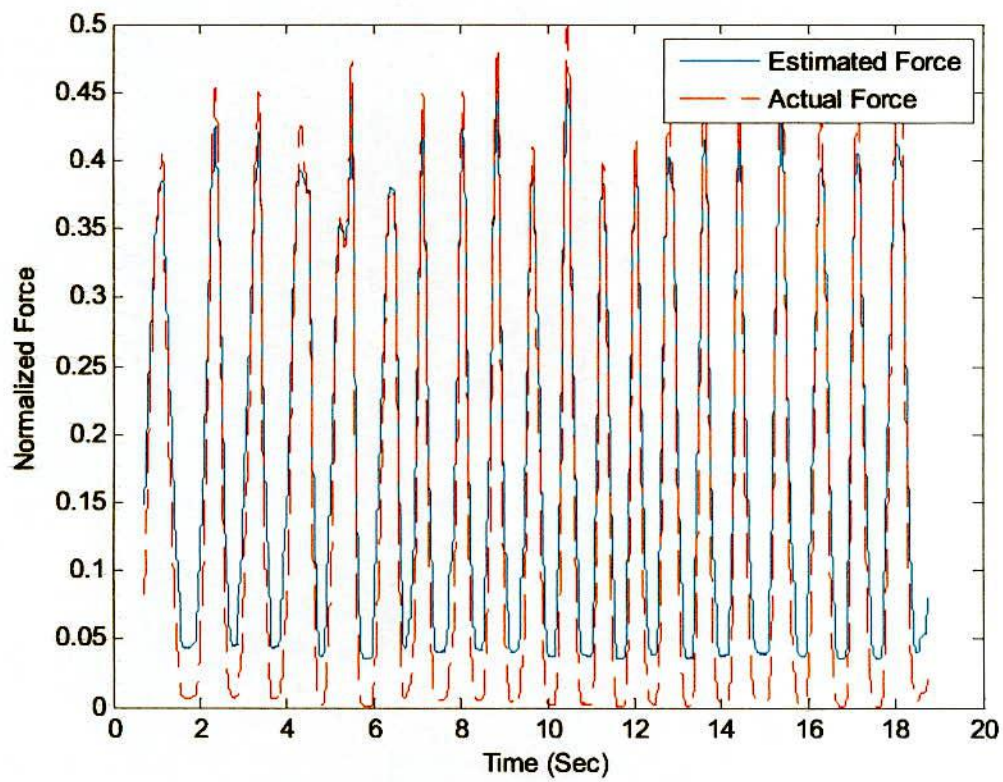


(e) For subject S5

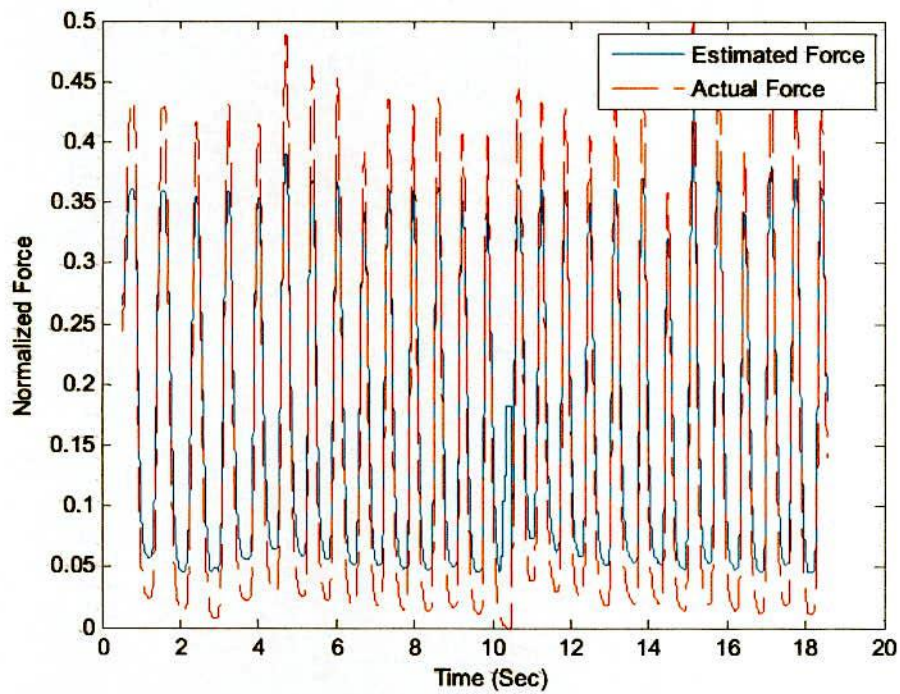
FIGURE 5.3 ACTUAL AND ESTIMATED FORCE USING RECTIFIED SEMG



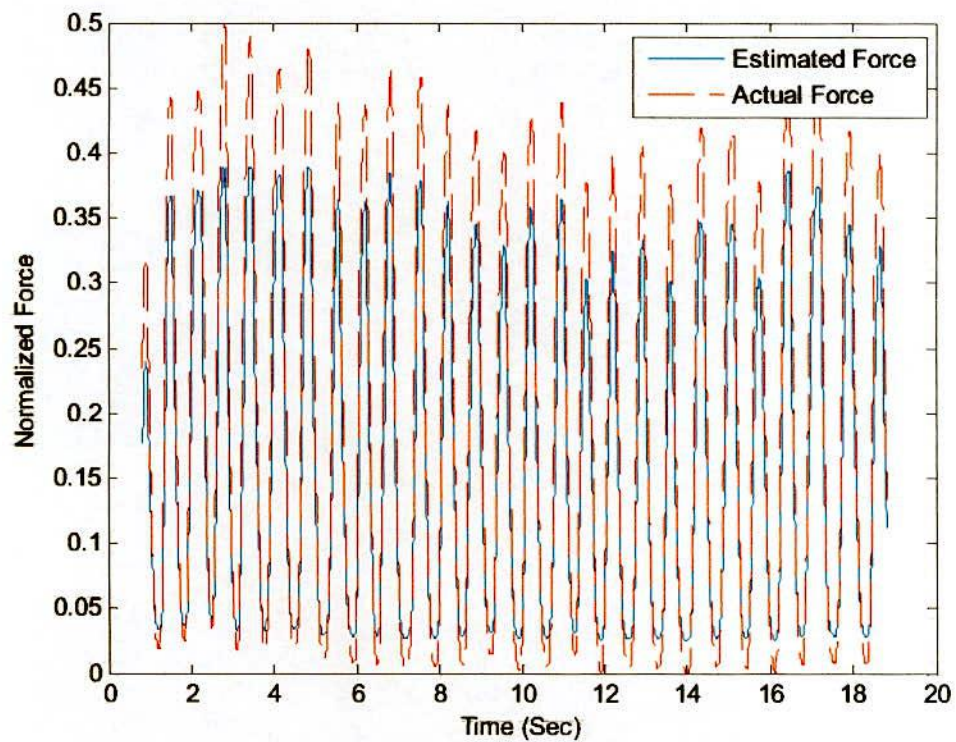
(a) For subject S1



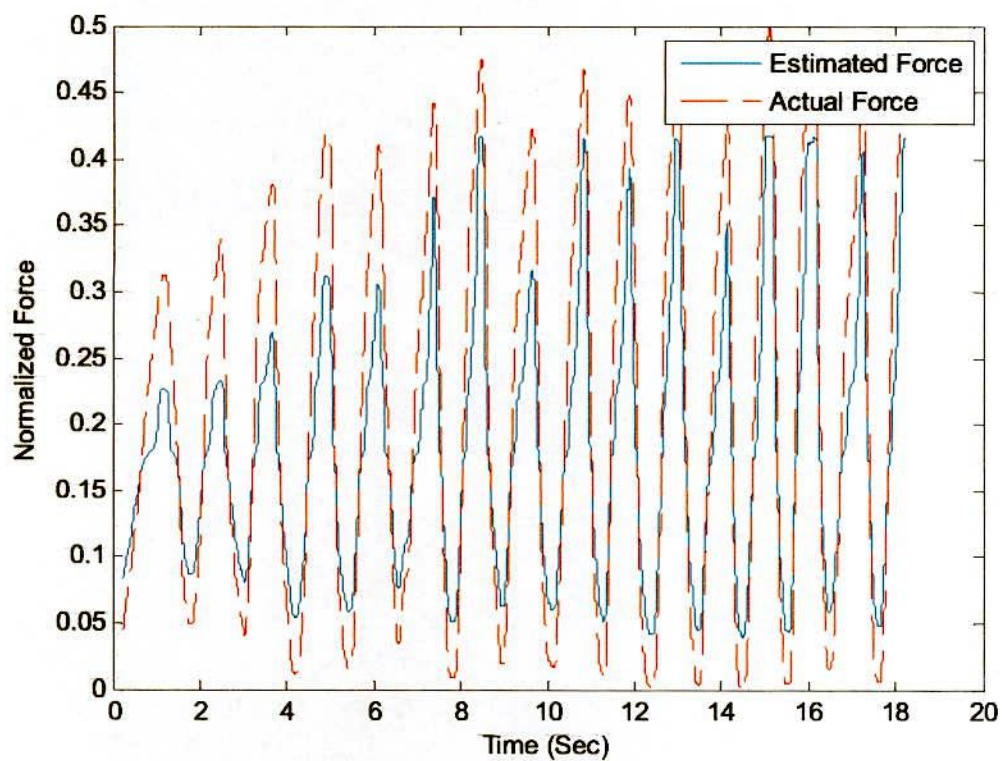
(b) For subject S2



(c) For subject S3

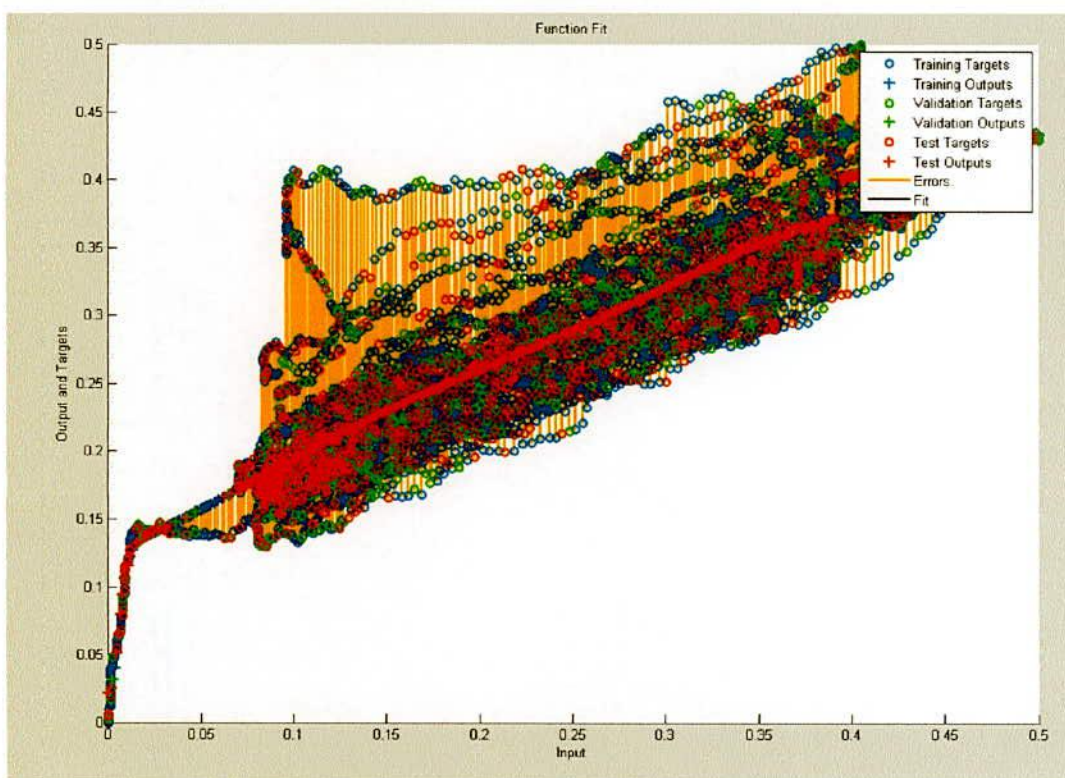


(d) For subject S4

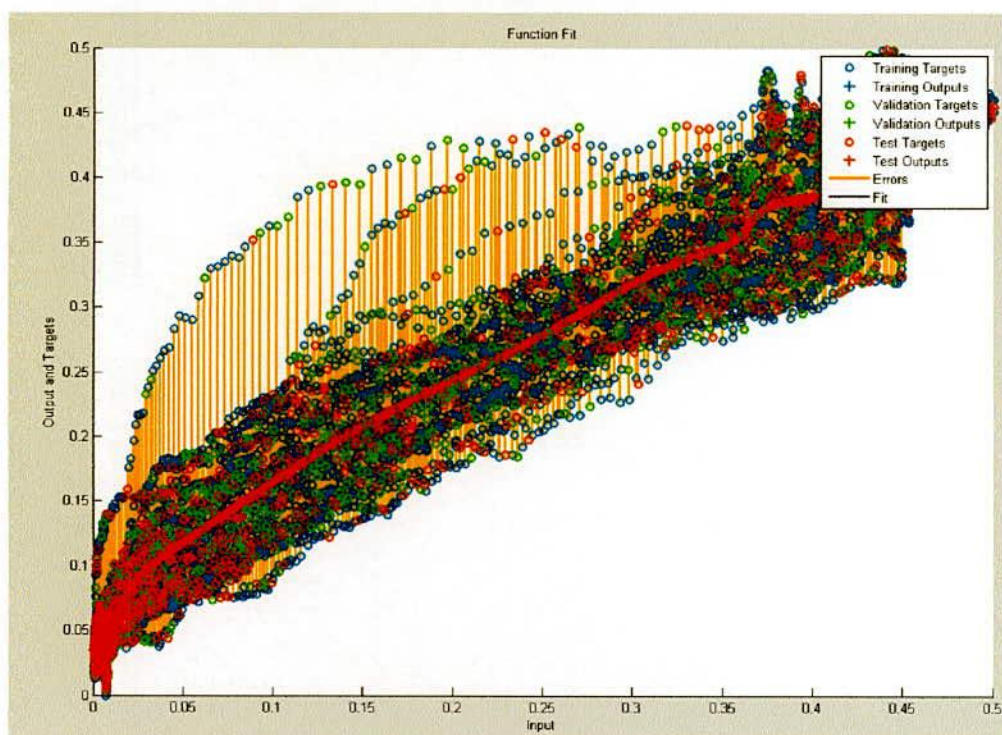


(e) For subject S5

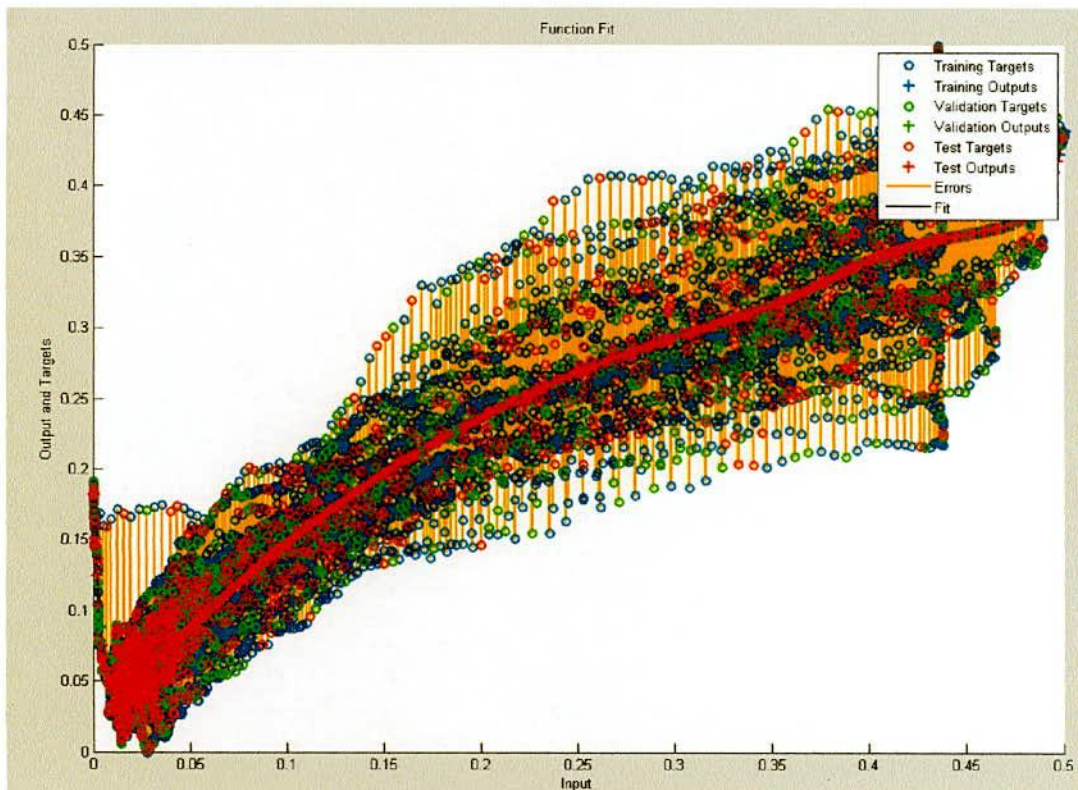
FIGURE 5.4 ACTUAL AND ESTIMATED FORCE USING INTEGRATED SEMG



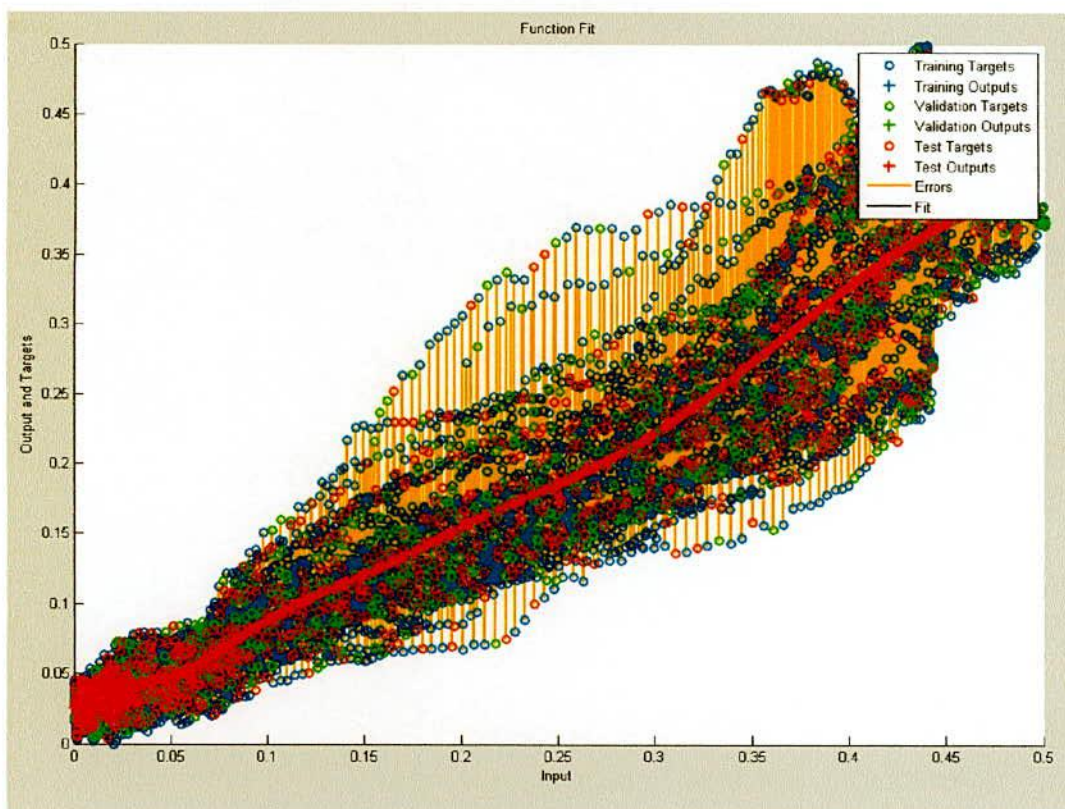
(a) For subject S1



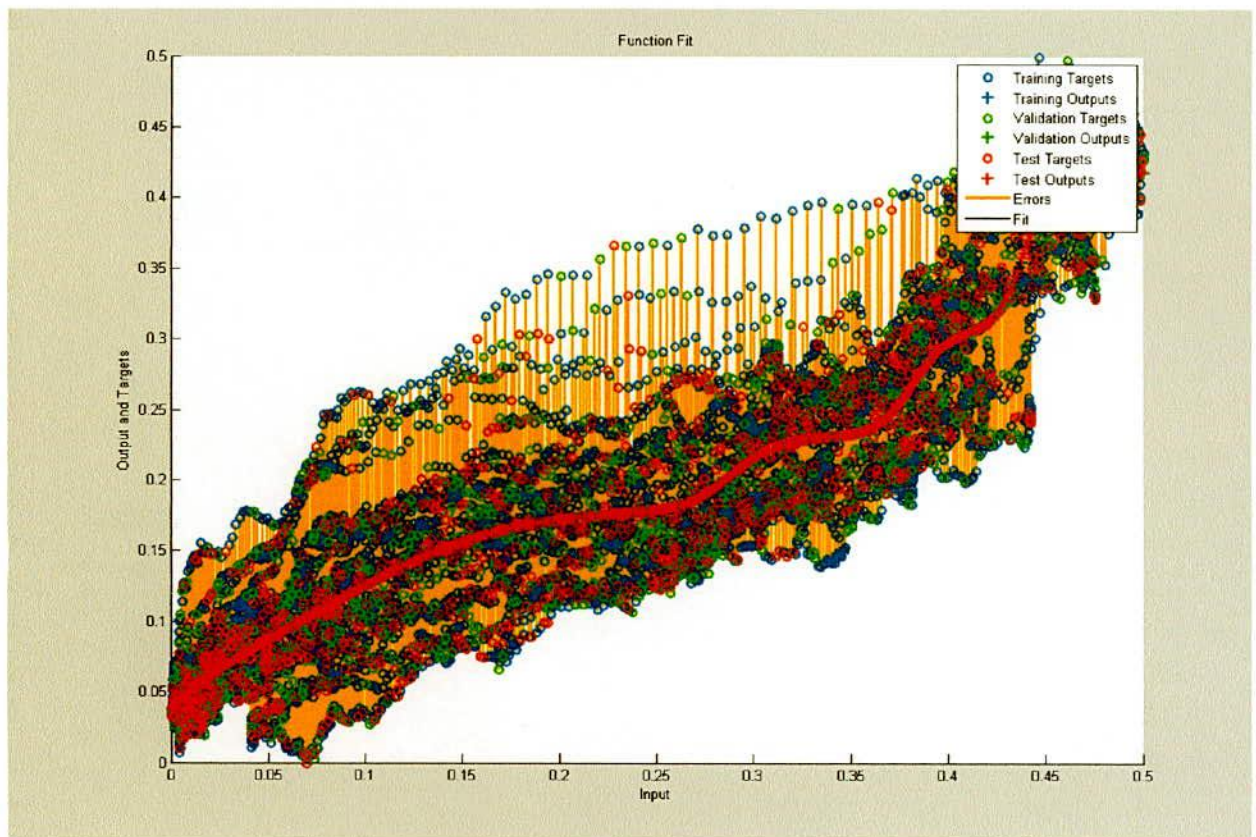
(b) For subject S2



(c) For subject S3

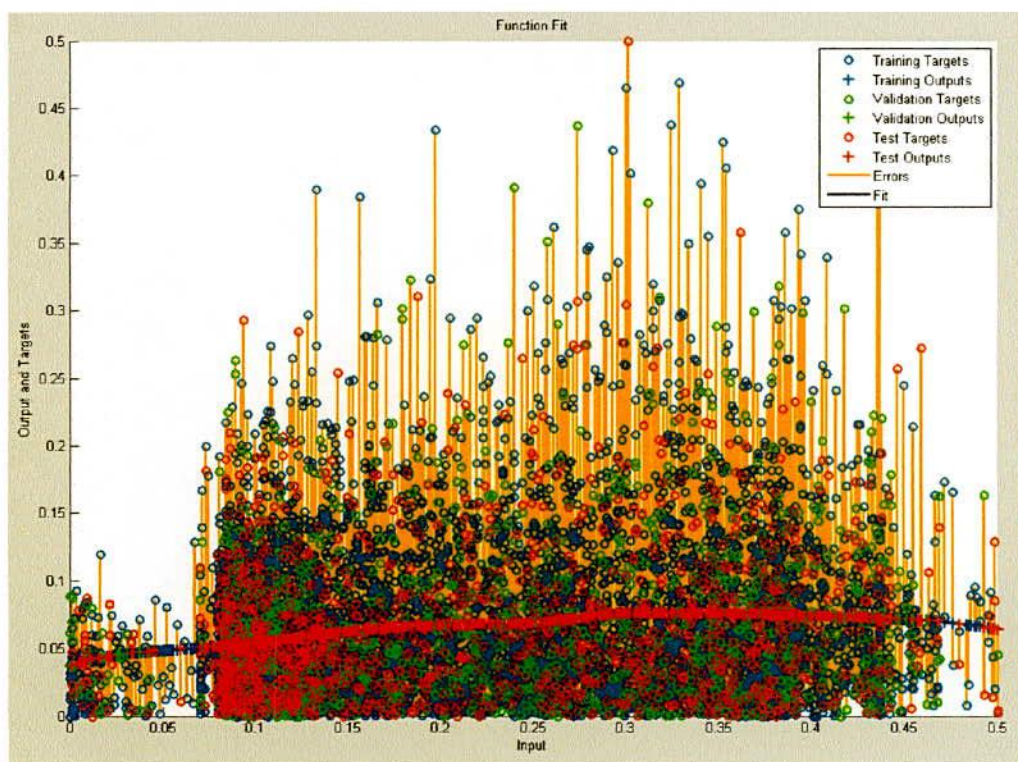


(d) For subject S4

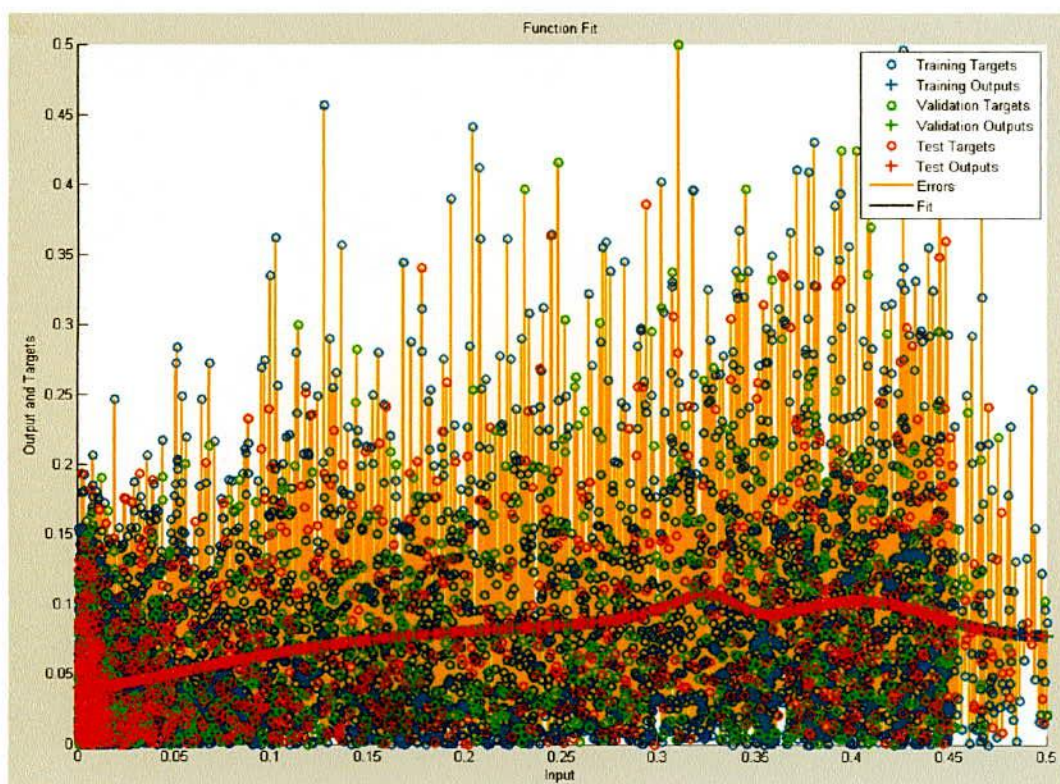


(e) For subject S5

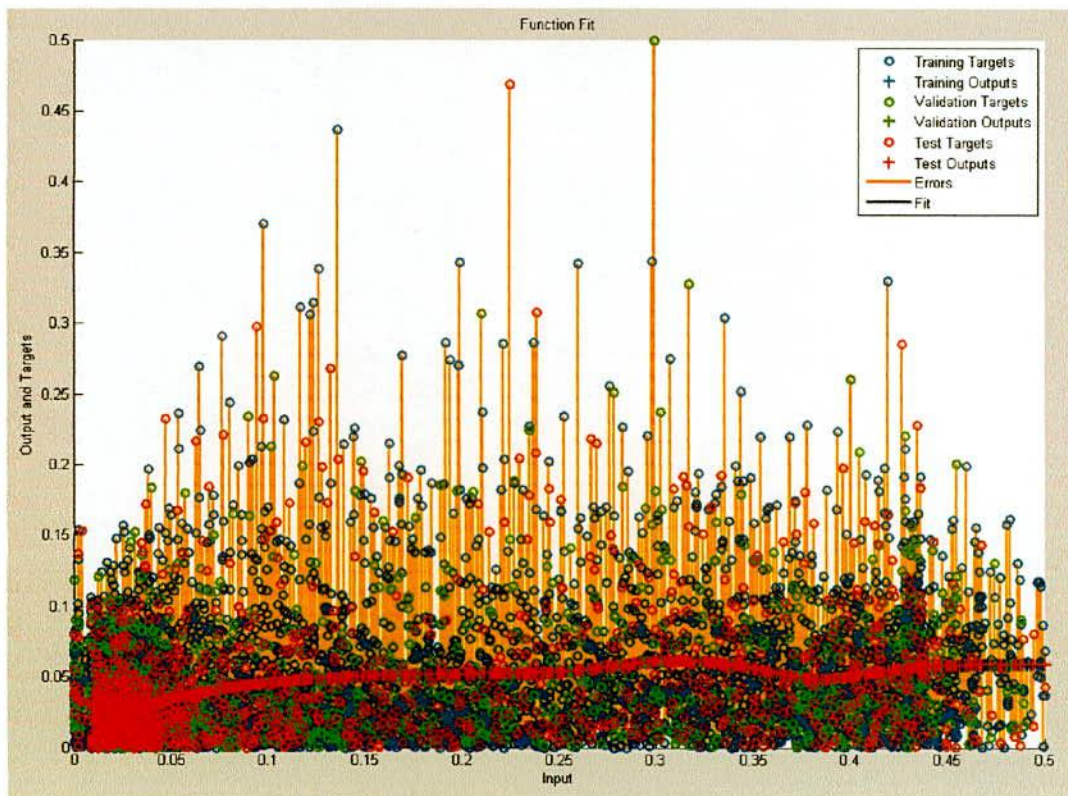
FIGURE 5.5 OUTPUT FUNCTION OF A NETWORK ACROSS THE RANGE OF THE INPUTS INTEGRATED SEMG AND TARGET FORCE AND OUTPUT DATA POINTS ASSOCIATED WITH VALUES OF INPUT INTEGRATED SEMG. ERROR BARS SHOW THE DIFFERENCE BETWEEN OUTPUTS AND TARGET FORCE



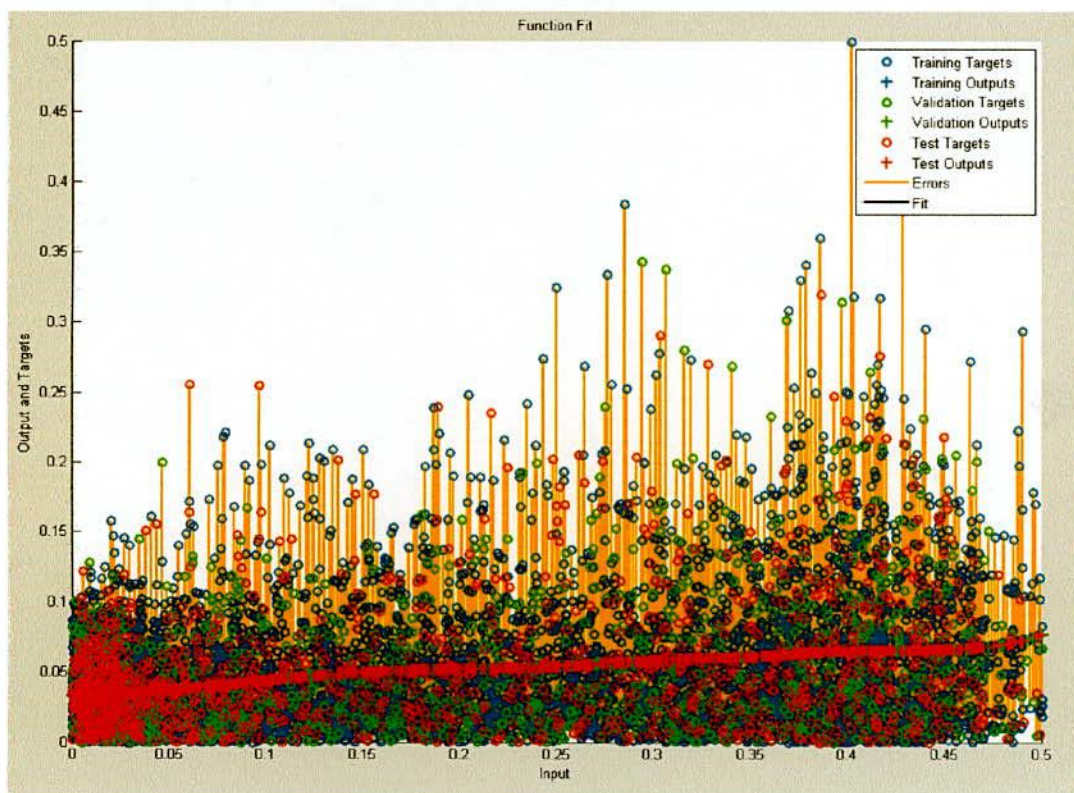
(a) For subject S1



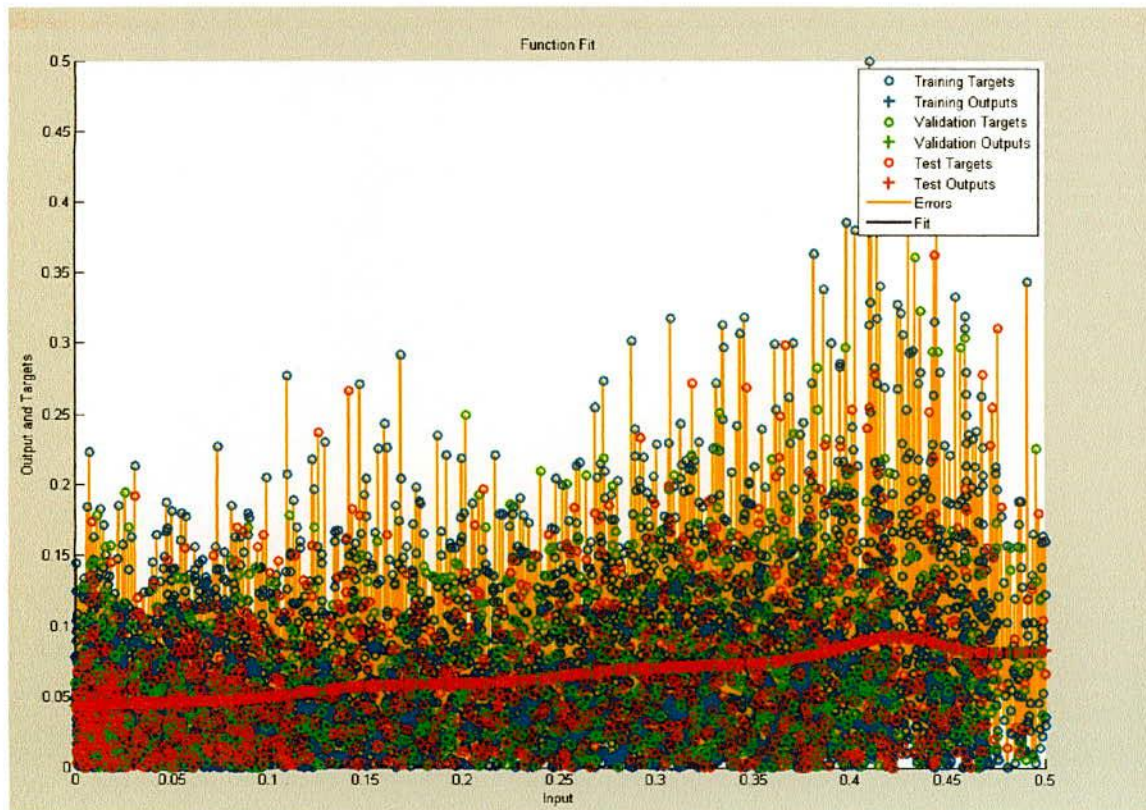
(b) For subject S2



(c) For subject S3



(d) For subject S4



(e) For subject S5

FIGURE 5.6 OUTPUT FUNCTION OF A NETWORK ACROSS THE RANGE OF THE INPUTS INTEGRATED SEMG AND TARGET FORCE AND OUTPUT DATA POINTS ASSOCIATED WITH VALUES OF INPUT INTEGRATED SEMG. ERROR BARS SHOW THE DIFFERENCE BETWEEN OUTPUTS AND TARGET FORCE

The experiment has been conducted using two types of SEMG, such as (i) rectified SEMG and (ii) integrated SEMG. The red dashed line represents the force measured from the sensor (hand dynamometer) and the blue solid line represents the force estimated by estimator ANN in Figure 5.3 and Figure 5.4. Figure 5.5 shows the performance of the rectified SEMG and Figure. 5.6 shows the performance of the integrated SEMG. The estimated results were quantitatively evaluated against the measured data using MSE and cross correlation coefficient (CORR) in Table 5.1, Table 5.2 and Table 5.3. In rectified SEMG, average MSE was 0.0199 and cross correlation coefficient 0.2664. For integrated SEMG, average MSE was 0.0030 and cross correlation coefficient 0.9403. It can be observed that integrated SEMG perform better than rectified SEMG as evidenced from Table 5.1, Table 5.2 and Table 5.3. For integrated

SEMG total estimator performance is shown in Figure 5.4. These tables also indicate that five neurons are enough for predicting clench force.

TABLE 5.1 TRAINING RESULT FOR RECTIFIED AND INTEGRATED SEMG IN FIVE SUBJECTS.

VALUES ARE DEMONSTRATED AS MSE AND CORR

Subject	For 50 neurons [86]				For 5 neurons			
	Training with Rectified SEMG		Training with Integrated SEMG		Training with Rectified SEMG		Training with Integrated SEMG	
	<i>MSE</i>	<i>CORR</i>	<i>MSE</i>	<i>CORR</i>	<i>MSE</i>	<i>CORR</i>	<i>MSE</i>	<i>CORR</i>
S1	0.0135	0.165	0.0024	0.903	0.02643	0.288	0.0021	0.907
	0.0134	0.157	0.0026	0.9	0.0258	0.287	0.00206	0.901
	0.0134	0.106	0.0025	0.907	0.0258	0.291	0.00208	0.905
S2	0.0228	0.211	0.0016	0.968	0.0373	0.382	0.00128	0.966
	0.0231	0.307	0.0016	0.967	0.0352	0.368	0.00131	0.965
	0.0231	0.316	0.0016	0.968	0.0367	0.370	0.00127	0.966
S3	0.0202	0.296	0.0017	0.959	0.0165	0.282	0.00130	0.954
	0.0205	0.282	0.0017	0.96	0.0168	0.278	0.00145	0.948
	0.0201	0.292	0.0017	0.96	0.0155	0.285	0.00133	0.954
S4	0.0204	0.299	0.0042	0.901	0.0185	0.278	0.00180	0.944
	0.0206	0.286	0.0042	0.902	0.0191	0.274	0.00177	0.945
	0.0205	0.285	0.0042	0.901	0.00190	0.270	0.00179	0.944
S5	0.0210	0.369	0.0016	0.967	0.0345	0.167	0.00144	0.895
	0.0210	0.394	0.0016	0.966	0.0319	0.166	0.00141	0.897
	0.0208	0.361	0.0016	0.966	0.0308	0.168	0.00144	0.896
<i>Average</i>	<i>0.0196</i>	<i>0.2751</i>	<i>0.0023</i>	<i>0.9397</i>	<i>0.0248</i>	<i>0.2769</i>	<i>0.0016</i>	<i>0.9325</i>

TABLE 5.2 VALIDATION RESULT FOR RECTIFIED AND INTEGRATED SEMG IN FIVE SUBJECTS.

VALUES ARE DEMONSTRATED AS MSE AND CORR

Subject	For 50 neurons [86]				For 5 neurons			
	Validation with Rectified SEMG		Validation with Integrated SEMG		Validation with Rectified SEMG		Validation with Integrated SEMG	
	MSE	CORR	MSE	CORR	MSE	CORR	MSE	CORR
S1	0.0138	0.168	0.0025	0.909	0.0253	0.277	0.00197	0.903
	0.0137	0.12	0.0022	0.915	0.0254	0.233	0.00212	0.901
	0.0131	0.165	0.0025	0.907	0.0275	0.268	0.00209	0.903
S2	0.0243	0.274	0.0017	0.971	0.0310	0.379	0.00134	0.965
	0.0241	0.263	0.0016	0.969	0.0388	0.410	0.00131	0.965
	0.0236	0.235	0.0017	0.966	0.0374	0.404	0.00144	0.961
S3	0.0208	0.248	0.0018	0.96	0.0153	0.260	0.00134	0.953
	0.02	0.314	0.0019	0.958	0.0134	0.269	0.00147	0.951
	0.0205	0.285	0.0018	0.957	0.0170	0.275	0.00137	0.951
S4	0.0207	0.25	0.0042	0.899	0.0191	0.269	0.00177	0.945
	0.0217	0.241	0.0041	0.904	0.0178	0.283	0.00193	0.940
	0.0207	0.281	0.0042	0.906	0.0185	0.276	0.00176	0.948
S5	0.0206	0.386	0.0017	0.965	0.0303	0.152	0.00143	0.893
	0.0199	0.394	0.0016	0.968	0.0348	0.160	0.00197	0.895
	0.0207	0.401	0.0016	0.967	0.0337	0.162	0.00149	0.892
Average	0.01988	0.268333	0.00234	0.940286	0.0257	0.2718	0.0017	0.9311



TABLE 5.3 TESTING RESULT FOR RECTIFIED AND INTEGRATED SEMG IN FIVE SUBJECTS.

VALUES ARE DEMONSTRATED AS MSE AND CORR

Subject	For 50 neurons [86]				For 5 neurons			
	Testing with Rectified SEMG		Testing with Integrated SEMG		Testing with Rectified SEMG		Testing with Integrated SEMG	
	<i>MSE</i>	<i>CORR</i>	<i>MSE</i>	<i>CORR</i>	<i>MSE</i>	<i>CORR</i>	<i>MSE</i>	<i>CORR</i>
S1	0.0129	0.127	0.0024	0.908	0.0251	0.260	0.00198	0.908
	0.0132	0.125	0.0024	0.908	0.0280	0.297	0.00213	0.902
	0.0136	0.123	0.0026	0.898	0.0255	0.268	0.00207	0.911
S2	0.0235	0.296	0.0017	0.966	0.0377	0.352	0.00130	0.965
	0.0224	0.317	0.0115	0.970	0.0398	0.391	0.00122	0.967
	0.0230	0.309	0.0016	0.968	0.0341	0.396	0.00121	0.964
S3	0.0200	0.305	0.0018	0.960	0.0161	0.293	0.00138	0.953
	0.0203	0.232	0.0018	0.969	0.0168	0.268	0.00143	0.949
	0.0207	0.278	0.0019	0.956	0.0186	0.301	0.00123	0.957
S4	0.0216	0.254	0.0042	0.904	0.0211	0.266	0.00185	0.943
	0.0205	0.277	0.0043	0.899	0.0192	0.230	0.00178	0.943
	0.0211	0.280	0.0043	0.897	0.0191	0.256	0.00185	0.942
S5	0.0208	0.367	0.0015	0.969	0.0295	0.151	0.00157	0.886
	0.0233	0.304	0.0017	0.963	0.0366	0.198	0.00165	0.877
	0.0220	0.402	0.0014	0.970	0.0327	0.157	0.00152	0.882
Average	0.0199	0.2664	0.0030	0.9403	0.0267	0.2723	0.0016	0.9299

TABLE 5.4 RESULT OF DIFFERENT LEAD POSITION FOR S2

<i>Lead position</i>	<i>Training</i>		<i>Validation</i>		<i>Testing</i>	
	<i>MSE</i>	<i>CORR</i>	<i>MSE</i>	<i>CORR</i>	<i>MSE</i>	<i>CORR</i>
111	0.00127	0.977	0.00097	0.980	0.00091	0.981
112	0.00168	0.961	0.00151	0.965	0.00156	0.964
113	0.00149	0.971	0.00157	0.969	0.00144	0.971
114	0.00145	0.970	0.00186	0.963	0.00150	0.968

121	0.00181	0.970	0.00199	0.953	0.00157	0.961
122	0.00139	0.962	0.00132	0.970	0.00143	0.968
123	0.00149	0.963	0.00128	0.968	0.00150	0.960
124	0.00156	0.968	0.00132	0.969	0.00150	0.965
131	0.00134	0.971	0.00127	0.969	0.00134	0.967
132	0.00120	0.971	0.00112	0.972	0.00119	0.971
133	0.00147	0.964	0.00153	0.964	0.00111	0.971
134	0.00067	0.980	0.00065	0.983	0.00646	0.982
141	0.00156	0.964	0.00174	0.953	0.00171	0.960
142	0.00169	0.963	0.00177	0.960	0.00167	0.964
143	0.00128	0.966	0.00099	0.971	0.00108	0.967
144	0.00138	0.966	0.00147	0.967	0.00146	0.964
211	0.00217	0.935	0.00219	0.930	0.00229	0.926
212	0.00193	0.950	0.00227	0.949	0.00207	0.945
213	0.00124	0.962	0.00151	0.956	0.00134	0.962
214	0.00110	0.944	0.00143	0.956	0.00129	0.962
221	0.00162	0.966	0.00188	0.941	0.00191	0.936
222	0.00144	0.962	0.00143	0.959	0.00197	0.964
223	0.00184	0.947	0.00198	0.940	0.00201	0.939
224	0.00166	0.962	0.00159	0.961	0.00170	0.959
231	0.00176	0.950	0.00222	0.938	0.00194	0.946
232	0.00182	0.942	0.00197	0.941	0.00173	0.949
233	0.00233	0.935	0.00239	0.929	0.00267	0.933
234	0.00149	0.956	0.00149	0.959	0.00155	0.956
241	0.00179	0.956	0.00172	0.960	0.00169	0.958
242	0.00141	0.958	0.00126	0.961	0.00153	0.957
243	0.00198	0.943	0.00186	0.954	0.00184	0.950
244	0.00222	0.941	0.00258	0.933	0.00247	0.934
311	0.00168	0.940	0.00210	0.933	0.00184	0.935
312	0.00126	0.963	0.00122	0.967	0.00140	0.962
313	0.00158	0.953	0.00165	0.948	0.00162	0.955
314	0.00164	0.955	0.00169	0.950	0.00183	0.956

321	0.00140	0.958	0.00139	0.958	0.00165	0.942
322	0.00170	0.957	0.00167	0.957	0.00163	0.957
323	0.00173	0.948	0.00148	0.952	0.00182	0.948
324	0.00160	0.959	0.00151	0.959	0.00167	0.960
331	0.00386	0.897	0.00383	0.903	0.00147	0.903
332	0.00172	0.957	0.00167	0.955	0.00168	0.959
333	0.00184	0.949	0.00193	0.949	0.00163	0.953
334	0.00167	0.954	0.00197	0.942	0.00180	0.950
341	0.00267	0.934	0.00232	0.938	0.00285	0.927
342	0.00196	0.944	0.00188	0.946	0.00183	0.948
343	0.00206	0.949	0.00194	0.938	0.00207	0.937
344	0.00159	0.956	0.00152	0.955	0.00165	0.954
411	0.00263	0.931	0.00269	0.934	0.00251	0.937
412	0.00128	0.958	0.00119	0.955	0.00111	0.960
413	0.00212	0.944	0.00202	0.944	0.00190	0.945
414	0.00174	0.942	0.00173	0.942	0.00179	0.943
421	0.00162	0.952	0.00154	0.953	0.00153	0.956
422	0.00146	0.960	0.00151	0.963	0.00137	0.965
423	0.00120	0.945	0.00196	0.944	0.00197	0.940
424	0.00135	0.953	0.00140	0.956	0.00162	0.952
431	0.00159	0.99946	0.00154	0.948	0.00150	0.952
432	0.00207	0.950	0.00197	0.954	0.00186	0.955
433	0.00148	0.951	0.00156	0.967	0.00143	0.948
434	0.00208	0.944	0.00201	0.942	0.00195	0.943
441	0.00179	0.939	0.00180	0.936	0.00192	0.933
442	0.00203	0.944	0.00228	0.933	0.00173	0.955
443	0.00162	0.956	0.00166	0.955	0.00156	0.953
444	0.00274	0.922	0.00255	0.926	0.00143	0.922
<i>Average</i>	<i>0.0017</i>	<i>0.9541</i>	<i>0.0017</i>	<i>0.9523</i>	<i>0.0018</i>	<i>0.9526</i>
<i>SD</i>	<i>0.00046</i>	<i>0.0148</i>	<i>0.00048</i>	<i>0.0144</i>	<i>0.00069</i>	<i>0.0144</i>

We can recall from Figure 4.3 which shows three electrodes position are marked with x, y and z and each of these electrodes have four individual position marked as 1, 2, 3 and 4

which creates total 64 combinations. The results of these combination are showed in Table 5.4. Lower SD values in every columns indicate that the lead displacements have a small effect on the result. Which is the indication of high fult tolerance of proposed system.

For support vector regressor nu-SVR with radial basis kernel is used.

TABLE 5.5 SVR TESTING RESULT FOR RECTIFIED AND INTEGRATED SEMG IN FIVE SUBJECTS.

VALUES ARE DEMONSTRATED AS MSE AND CORR

Subject	Testing with Rectified SEMG		Testing with Integrated SEMG	
	<i>MSE</i>	<i>CORR</i>	<i>MSE</i>	<i>CORR</i>
S1	0.0115257	0.014868	0.00125769	0.913928
	0.0115257	0.014868	0.00125769	0.913928
	0.0115257	0.014868	0.00125769	0.913928
S2	0.022774	0.144527	0.00176561	0.934297
	0.022774	0.144527	0.00176561	0.934297
	0.022774	0.144527	0.00176561	0.934297
S3	0.0221278	0.0639207	0.00310627	0.871534
	0.0221278	0.0639207	0.00310627	0.871534
	0.0221278	0.0639207	0.00310627	0.871534
S4	0.0229988	0.0670427	0.0191946	0.943903
	0.0229988	0.0670427	0.0191946	0.943903
	0.0229988	0.0670427	0.0191946	0.943903
S5	0.0275258	0.0839839	0.00669008	0.841156
	0.0275258	0.0839839	0.00669008	0.841156
	0.0275258	0.0839839	0.00669008	0.841156
Average	0.021390	0.0748685	0.00640285	0.9009636

From table 5.3 and table 5.5 neural network perform better compared to support vector regression both in rectified and integrated SEMG

CHAPTER 6

Conclusions & Future Works

6.1 Conclusions

The past decade has seen a fast proliferation of neural networks in control applications, particularly for robotics. Neural networks are attractive for control because of their high speed computation, a high degree of fault tolerance due primarily to their parallel structure, and the ability for adaptive learning. In other applications, neural networks are used to store a vast amount of past control experience and retrieve motor commands by searching for the nearest experience. These approaches to motor control using artificial neural networks are conceivably applicable to electrical stimulation of muscles in neural prosthesis systems. The results in this study demonstrate that it is possible to use an artificial neural network to implement an optimal control strategy for force prediction.

A practical issue in force control is how a neural network can be used to perform a specific force. In most cases, the method used to train the neural network is largely left to the nature of individual applications. Furthermore, the neural network can be trained off-line and more effectively adapted on-line during real time control. For training the neural network, information obtained during motor performance by normal human subjects replicates the features of voluntary movements that were employed. This idea has led to an investigation of a minimal effort control strategy for the force prediction of muscle controls. This model has successfully duplicated the key behaviors of force of voluntary movements.

We compared different neural network architectures for their learning performance. We have found that Levenberg-Marquardt (L-M) back propagation significantly improves the speed of learning over the pure feed forward network. We observed that the pure feed forward networks were not efficient for learning SEMG signals. Its learning speed was very slow and the convergence depended heavily on the initial assignments of weights.

The human body as a whole is electrically neutral. A muscle is composed of bundles of specialized cells capable of contraction and relaxation. This depolarization, accompanied by a movement of ions, generates an electric field near each muscle fiber. An EMG signal is the

train of Motor Unit Action Potential (MUAP) showing the muscle response to neural stimulation.

In this research, two types of SEMG are used to estimate the clench force. Our experiments showed that an ANN estimator using the SEMG was successfully estimated the clench force. Number of neuron in hidden layer was found in the experiment, the number was five. It is well known that lower value of MSE and higher value of CORR are desirable. From the result, it is observed that in the case of integrated SEMG, the CORR value is high and MSE value is 7.56 times lower compared to rectified SEMG. So integrated SEMG is more perfect a choice than rectified SEMG to estimate clench force. However, the major contribution of this work is to estimate clench force using ANN estimator. More over the fault tolerance of the system also found high. The tolerance was tested by misplacing the leads, system gave almost same output in faulty lead positions.

Support Vector Regression (SVR) have found increasing consideration in forecasting theory, leading to successful applications in time series and explanatory forecasting in various domains, including business and management science. That is why SVR is used to compare neural network results. In the case of integrated SEMG, SVR and ANN's performance is quite same (i.e. CORR is 0.9009636 and 0.9299 respectively). However when rectified SEMG ANN's performance comes is better than SVR's.

6.2 Future Works

The MSE and CORR achieved here is state of art and these values will allow future comparison with others. In future, proposed method can be extended to other types of grip force estimation. It may be denoised SEMG which will give better result compared to present approach, which is also under consideration.

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APPENDIX I

Collected data sample for S1

Time (sec)	Force (Kg)	EMG (mv)	Integrated EMG(mv)
0	-0.01753	0.029297	0
0.002	-0.01753	0.033569	0.000293
0.004	-0.01753	-0.04578	0.000629
0.006	-0.01753	0.073242	0.001086
0.008	-0.01753	-0.01892	0.001819
0.01	-0.01753	0	0.002008
0.012	-0.01753	-0.01465	0.002008
0.014	-0.01753	0.105591	0.002155
0.016	-0.01753	-0.03906	0.00321
0.018	-8.78E-05	-0.00488	0.003601
0.02	-8.78E-05	-0.00305	0.00365
0.022	-8.78E-05	0.053101	0.00368
0.024	-8.78E-05	-0.03113	0.004211
0.026	-8.78E-05	0.078125	0.004523
0.028	-8.78E-05	-0.03906	0.005304
...	...	...	...
10.058	4.98736	0.038452	0.093616
10.06	4.95248	0.010376	0.091119
10.062	4.9176	-0.02136	0.090338
10.064	4.88272	-0.04822	0.088702
10.066	4.84785	-0.03296	0.086816
10.068	4.81297	0.013428	0.085626
10.07	4.76065	0.078125	0.085846
...	...	...	...
17.986	2.21462	0.090332	0.074091
17.988	2.1623	-0.03784	0.073505
17.99	2.12742	0.031738	0.072003
17.992	2.07511	0.054932	0.072003
17.994	2.04023	0.049439	0.072339
17.996	2.00535	-0.06042	0.06958
17.998	1.97048	0.068359	0.068671

Collected data sample for S2

Time (sec)	Force (Kg)	EMG (mv)	Integrated EMG(mv)
0.722	2.00536	0.01709	0.059638
0.724	2.05768	-0.08545	0.059949
0.726	2.12743	-0.08789	0.059442
0.728	2.17975	0.06958	0.060095
0.73	2.23206	-0.0116	0.059851
0.732	2.28438	0.01648	0.0599
0.734	2.33669	0.024414	0.059076
0.736	2.37157	0.094605	0.059241
0.738	2.42389	-0.00366	0.05907
0.74	2.4762	-0.00305	0.058557
0.742	2.51108	0.053711	0.058991
0.744	2.56339	0.018921	0.058185
0.746	2.61571	0.098267	0.059039
0.748	2.66803	0.162964	0.060449
0.722	2.00536	0.01709	0.059638
...	...	...	...
12.158	4.72578	-0.00488	0.077643
12.16	4.58627	0.023193	0.077564
12.162	4.44677	-0.1001	0.078253
12.164	4.30726	0.023193	0.076709
12.166	4.16775	0.041504	0.076221
12.168	4.04568	0.018921	0.075617
12.17	3.92361	0.015869	0.074939
...	...	...	...
18.686	0.10455	-0.07141	0.037097
18.688	0.10455	0.039673	0.036835
18.69	0.087111	-0.04456	0.036823
18.692	0.10455	0.015869	0.036829
18.694	0.10455	0.009766	0.036829
18.696	0.121989	-0.01038	0.036499
18.698	0.139427	-0.1178	0.03747

Collected data sample for S3

Time (sec)	Force (Kg)	EMG (mv)	Integrated EMG(mv)
0.538	5.07456	0.22644	0.089417
0.54	5.14432	0.233765	0.091254
0.542	5.21407	-0.09216	0.092011
0.544	5.26639	-0.07263	0.092059
0.546	5.33614	0.065918	0.092297
0.548	5.38846	0.15686	0.092267
0.55	5.44077	-0.04639	0.092133
0.552	5.49309	0.079956	0.092426
0.554	5.5454	-0.09216	0.091406
0.556	5.59772	-0.1239	0.092151
0.558	5.66747	-0.09583	0.092835
0.56	5.71979	-0.05554	0.093292
0.562	5.77211	-0.03357	0.092896
0.564	5.82442	0.257568	0.09447
0.566	5.87674	0.131226	0.095123
.....			
6.042	9.19007	-0.05371	0.142822
6.044	9.13776	-0.07446	0.142059
6.046	9.08544	-0.05859	0.142474
6.048	9.05057	-0.0354	0.140344
6.05	8.99825	-0.08545	0.140527
6.052	8.9285	-0.07874	0.139539
6.054	8.87618	0.037842	0.138068
.....			
18.476	6.26039	-0.12634	0.097168
18.478	6.15576	-0.01648	0.096246
18.48	6.03368	-0.23071	0.09762
18.482	5.91161	-0.10132	0.094617
18.484	5.78954	-0.06836	0.093732
18.486	5.66747	-0.03601	0.093732
18.488	5.5454	-0.15442	0.095111

Collected data sample for S4

Time (sec)	Force (Kg)	EMG (mv)	Integrated EMG(mv)
0.816	4.67344	0.078125	0.166254
0.818	4.77807	0.24292	0.166791
0.82	4.90014	-0.05493	0.165985
0.822	5.00477	-0.1239	0.165289
0.824	5.12684	-0.27039	0.166437
0.826	5.23148	-0.24536	0.167017
0.828	5.31867	-0.57861	0.170258
0.83	5.4233	-0.27649	0.171637
0.832	5.51049	-0.03479	0.171423
0.834	5.59769	0.291138	0.171893
0.836	5.70232	0.22644	0.172003
0.838	5.80695	0.015259	0.172095
0.84	5.89414	-0.06714	0.172565
0.842	5.99878	0.128174	0.172638
0.844	6.08597	-0.27466	0.173358
.....			
12.048	2.14484	-0.31982	0.128607
12.05	2.28435	-0.04456	0.128076
12.052	2.40642	-0.11597	0.127655
12.054	2.51105	0.15564	0.128705
12.056	2.61568	0.022583	0.128009
12.058	2.73775	0.209961	0.12843
12.06	2.84239	-0.23865	0.129999
.....			
18.772	4.4293	0.043945	0.1724
18.774	4.30723	0.215454	0.173792
18.776	4.18516	-0.37109	0.174689
18.778	4.06309	0.03418	0.174188
18.78	3.95846	-0.20996	0.172827
18.782	3.81895	-0.11841	0.172717
18.784	3.69688	-0.16602	0.171838

Collected data sample for S5

Time (sec)	Force (Kg)	EMG (mv)	Integrated EMG(mv)
0.226	1.39501	0.001831	0.066321
0.228	1.41245	0.114136	0.067346
0.23	1.42988	-0.02686	0.065692
0.232	1.44732	0.101318	0.066425
0.234	1.46476	-0.05188	0.066888
0.236	1.4822	0.048828	0.067047
0.238	1.49964	-0.05432	0.067279
0.24	1.49964	-0.01282	0.065076
0.242	1.51708	-0.20142	0.066504
0.244	1.51708	-0.00916	0.066229
0.246	1.51708	-0.02319	0.066065
0.248	1.53452	0.032349	0.065546
0.25	1.55195	-0.04334	0.064038
0.252	1.55195	0.180054	0.065436
0.254	1.56939	-0.04089	0.065479
...	...	...	...
4.36	1.56939	-0.17639	0.08501
4.362	1.58683	-0.04211	0.083875
4.364	1.60427	-0.12695	0.083691
4.366	1.63915	-0.15137	0.085004
4.368	1.67403	-0.23804	0.086456
4.37	1.69146	-0.31616	0.08916
4.372	1.72634	-0.11353	0.08988
...	...	...	...
18.21	10.5328	0.057373	0.156903
18.212	10.5154	0.020752	0.153601
18.214	10.5154	0.039673	0.153723
18.216	10.5154	0.26062	0.155847
18.218	10.5154	0.494995	0.160455
18.22	10.5154	0.033569	0.158148
18.222	10.5154	-0.30701	0.16048

APPENDIX II

Sample Data collection sheet

Data collection number: _____



Department of Biomedical Engineering

Khulna University of Engineering & Technology

Subject name: Shahin, Shahin

Age: 25 Height: 5'7" Weight: 56

Gender: ☒ M ☐ F Email: shahin@jahes.com Mobile number: 01914666666

Address: 44, Road, Khulna - 9100

Other information (if required): _____

Dominate forearm: ☐ L ☒ R

	Data Type	File name	Condition
1.	EMG	Shahin - R1	*
2.	✓	Shahin - R2	*
3.			
4.			
5.			
6.			
7.			

Declaration

I hereby declare that, I voluntary participate the test and know the risk associated with the test. Data collected from the test can be used without my permission for any revised or extended derivative work based on this data and/or any associated written, audio and /or visual presentation or other for research and publication.

Signature: [Signature]

Date: 12 / 11 / 2011 (DD/MM/YYYY)

Data capture by: 12/11/2011

Shahin