ELECTROENCEPHALOGRAM BASED EXOSKELETON FOR FINGER REHABILITATION

PROJECT REPORT

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF

Bachelor of Technology

in

Mechanical Engineering

Submitted By

SHEERAZ ATHAR **AHMAD RAZA USMANI**

Under the supervision of

DR. M. MUZAMMIL

DEPARTMENT OF MECHANICAL ENGINEERING
ZAKIR HUSAIN COLLEGE OF ENGINEERING & TECHNOLOGY
ALIGARH MUSLIM UNIVERSITY ALIGARH
ALIGARH-202002 (INDIA)
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15MEB550

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STUDENTS’ DECLARATION

I hereby certify that the work, which is being presented in this project report, entitled, **“Electroencephalogram based exoskeleton for finger rehabilitation”** is in partial fulfilment of the requirements for the award of the Degree of Bachelor of Technology and is submitted in the Department of Mechanical Engineering of the Zakir Husain College of Engineering & Technology, Aligarh Muslim University, Aligarh. This is an authentic record of our own work carried out during final year of B. Tech. under the guidance of **Dr. M. Muzammil**, Professor, Department of Mechanical Engineering, Aligarh Muslim University, Aligarh.

(Sheeraz Athar) **(Ahmad Raza Usmani)**

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

(Dr. M. Muzammil)
Project Guide

Date:

ABSTRACT

More than 200 million people worldwide live with some type of disability, with a large number of people having motor disabilities. This hinders their ability to perform daily activities of life. Rehabilitation is a technique through which this lost motor functioning can be regained. In rehabilitation the affected part is subjected to continuous passive motions, this exploits the plasticity trait of human brain in achieving back the lost motion. Exoskeleton have potential capabilities to provide rehabilitation. Several studies in the past have utilised exoskeletons to provide the same.

In the proposed study, we have designed an exoskeleton consisting of the following parts *Circular part*, *Linkage structure*, *Base.* For calculating the dimensions of linkages we used anthropometric data of human finger and dynamically simulated the model to testify that the designed part is mimicking the natural trajectory of human hand. Static simulation of the designed model is also carried out to assess the structural strength. In the simulation results, all the design parameters comes well under stipulated limits.

For actuation and control, we proposed the use of microcontrollers coupled with Brain Machine Interface (BMI). The different stages of BMI include Signal acquisition, feature extraction, feature selection and classification. The EEG dataset used in this work was created by the University of Tubingen, Germany. EEG signals associated with the imagined movement of right hand and relaxation state were processed using wavelet transform analysis for feature extraction. The optimum classification performance of 82.911% was achieved with a random forest classifier.

As a Future prospect this classified data can be utilised to programme a microcontroller linear actuator named Firgelli for the execution of different tasks.

ACKNOWLEDGEMENTS

In the name of Allah, Most Gracious, Most Merciful

We would like to express our deepest gratitude to our supervisor **Dr. M. Muzammil** for his inspiration and encouragement in the successful completion of this work. He has always been cordial, attentive, responsible and supportive throughout all the highs and lows during the journey. We are highly indebted to him for his guidance and constant supervision as well as for providing necessary information regarding the project & for his support in completing the project. We would also like to extend our sincere gratitude to him for providing his invaluable guidance, comments and suggestions throughout the course of the project. He invested a lot of his time for our work, giving valuable inputs and took great pains to see us through. Without his knowledge and guidance, this project would not have been possible. We have learnt a lot from him and we humbly acknowledge a lifetime deep gratitude to him. He devoted a lot of time and patience to the reading and correction of this work. Also, we would like to acknowledge the unconditional help rendered to us by **Mr. Siddhartha Bharadwaj**, PhD candidate, MED, AMU. Apart from this, we are also extremely thankful to **Dr. Omar Farooq** and his student **Mr. Bilal Alam Khan**, both from ELED, AMU, for their expert guidance and help during the course of this study.

Finally, we wish to thank our parents, brothers and sisters for their constant support and encouragement and the motivation they provided which kept us going even in the hard times.

Date: (Sheeraz Athar, Ahmad Raza Usmani)

Place:

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LIST OF SYMBOLS

F1	IQR
F2	MAD
F3	Mean Absolute Value
F4	Variance
F5	Skewness
F6	Kurtosis
F7	Energy
F8	Standard Deviation

LIST OF ABBREVIATIONS

EEG	Electroencephalogram
EMG	Electromyography
BCI	Brain Computer Interface
MI	Motor Imagery
RF	Random Forest
MCP	Metacarpophalangeal joint
PIP	Proximal Interphalangeal joint
DIP	Distal Interphalangeal joint
MED	Mechanical Engineering Department
AMU	Aligarh Muslim University
ELED	Electronics Engineering Department

Chapter 1

Introduction

The ability to move is essential for basic activities in everyday life. Several motor dysfunctions significantly reduces the patient's quality of life. A disabled member loses his independence in particular. Stroke, Myoclonus, Huntington's disease, etc. are the main causes of motor dysfunction. In addition, various traumatic accidents lead to injury, resulting in temporary loss of exercise. In all of these cases, the patient is in great need of returning to a normal state. Rehabilitation is the process used to restore the flexibility of the affected part.

Motorized repetitive exercises for human joints have proven to be an effective solution for the recovery of lost motion. Recent technological advances have focused on functional exercises to restore the motion of upper and lower limbs. The number of patients requiring physical rehabilitation of the upper limbs has increased dramatically. This phenomenon automatically leads to an increase in the number of therapists and caregivers who help the physically disabled at home, which may become a serious problem in the near future. Rehabilitation robot systems can be considered an effective solution to this type of problem. However, the availability of these devices is still limited and there is more work in one area. The main purpose of this work is to provide robotic solutions by attempting to improve existing upper limb rehabilitation.

1.1 Overview and Motivation of the Study

Neuro-rehabilitation has been identified as a major challenge in the current era, mainly because the population of people affected with neurological disorders (e.g., stroke, Alzheimer, and Parkinson) is rapidly increasing. According to the latest data from Medical News Today, 5 million people in the United States have some type of serious body paralysis [1]. Currently, there is no method to cure this devastating paralysis case, such as complete spinal cord injury (SCI) [2]. It has been reported by CDC that more than 17 million people found it difficult to stroll even a short distance of quarter mile. Stroke is the leading cause of disability worldwide [3]. Hemiparesis or unilateral paresis is one of the most common aftermath of stroke causing weakness of the muscles leading to an abnormal posture, movement disabilities, thus degrading the quality of life of stroke/trauma patients [4]. Hemiparesis in its most unpleasant form causes one side of the body to be paralyzed resulting in reduced muscle strength. Because of which, people with hemiparesis find difficulty in accomplishing their daily life activities such as walking, grasping objects, etc. [5]. The mortality rate is 50% and those who survive, survives with a permanent disability [6]. The initial treatment provided to these stroke/trauma patients is in the form of physical therapy so that they can perform their basic daily life activities. Treatment through exercises, physical therapy or rehabilitation clinics to some extent help in easing their lives by enabling them to use wheelchairs, walking on their own, moving upstairs, etc. However, the percentage of post stroke/trauma patients able to perform these tasks is quite depressing [7]. Hence, there is an urgent need for effective, quantitative and automated rehabilitation services to meet the growing demand for long-term medical treatments and healthcare, and to compensate the lack of work force in rehabilitation professionals.

Robotic Exoskeletons are a viable solutions to these problems. Robot comes with numerous inherent advantages such as high adaptivity, better precision and control. As a result, more effective and autonomous rehabilitation devices can be constructed.

1.2 Problem formulation

Our research aims to carry out the design and development of a hand exoskeleton which could be used for providing rehabilitation to the patients with motor dysfunctions.

Due to various disorders, trauma, and accidents, many individual lose their full potential mobility, due to which they are unable to do daily living tasks. They usually depend on others for all the activities, thus, they lose their physical independence.

Rehabilitation is the procedure through which motor recovery can be achieved.

Conventional rehabilitation techniques are cumbersome and require at least one person to assist the patient during the rehabilitation. This creates lack of interest on the patients' part, as conventional methods are not interactive, also it poses a big problem of employing at least on attendant with every patient.

Considering all this, robotic-assisted devices give a very valuable alternative. Robots usually have better control and adaptively. Due to these qualities, robotic exoskeleton is now widely used as a rehabilitation device.

Using exoskeleton devices for rehabilitation provides better handling and interactive mechanism. As most of the exoskeleton devices are automated, they eliminate the need of a medical attendant during the rehabilitation. Also, robotic exoskeletons keep a record of a person's recovery which helps in analyzing the performance.

1.3 Organization of the Thesis

This work consists of six chapters and is structured as follows:

Chapter 1 shows the Introduction and Overview and Motivation of this study.

Chapter 2 focuses on the literature review done. This chapter shows the significant advances made in the exoskeleton based rehabilitation devices over the time.

Chapter 3 presents the methodology used in this study. It talks about the design, simulation and manufacturing of the exoskeleton device. It also discusses the actuation mechanism involved.

Chapter 4 discusses the controlling part of the exoskeleton, and introduces EEG. It tells us about the EEG signal recording, feature extraction and classification

Chapter 5 presents the results of the current work. It includes the results of static simulation, dynamic simulation and feature classification.

Chapter 2

Literature Review

Several ways to restore upper limb function has been introduced in the literature. The orthosis can solve the problem of upper limb disability. Electrical stimulation is one of the techniques used for treatment and rehabilitation. Physical therapy remains one of the most effective techniques for dealing with disability issues. All kinds of work are concentrated on upper limb rehabilitation [8], [9], [10], [11], [12], [13], [14], [15]. Further research focused only on the rehabilitation of elbow joints [16], [17], [18], [19], [20], [21], [22], [23], [24], [25] , [26] or hand [27], [28], [29], [30], [31]. In order to overcome the problem of perceived processing defects, an innovatively integrated setup was proposed in [31] to provide users with EMG-based visual-tactile biofeedback. In [27], the authors present clinical evidence of the contribution of robots to the improvement of hand movement recovery in acute stroke patients. The ARAMIS (Automatic Arm Mobile Integrated System) project [32] developed a new rehabilitation exoskeleton design with multidisciplinary support and rehabilitation training specifically for upper limbs after stroke [32]. In the handwriting of children who have improved motor skills, the efficacy of robotics is explored [29]. In [33], the authors proposed an assisted torque system with a uniform surface electromyography (EMG) signal to improve the elbow torque capability of stroke patients. The EMG-based robotic hand device is envisioned to provide training for injured hands after a stroke [31]. The Supinator Extender (SUE) is a 2-DOF continuous pneumatic robot for measuring and assisting forearm supination - internal rotation and wrist flexion and extension [33]. [34]

presented a brief report of clinical experience involving the improvement of upper limbs in patients with stroke-related lesions assisted by robotics. The modeling, design, and control of the 2DOF exoskeleton robot (ExoRob) were developed in [35], [36], [37] to repair the elbow and forearm movements of physically disabled persons with impaired upper limb function. Based on the servo motor's application of torque to the elbow, Cozens JA developed a simple system in [16] that demonstrated an increase in the average range of active stretch buckling for each group of 10 patients. The author of [18] introduced a new design for an intelligent portable rehabilitation device that has real-time monitoring capabilities that can significantly improve the recovery process.

Wearable interaction systems are being used these days for the rehabilitation. There have been many attempts to develop wearable interaction systems for the hand. Previously developed systems can be categorized into (1) cable-driven glove systems, (2) cable-driven frame systems, and (3) exoskeleton systems by their structures and actuating mechanisms.

As a cable-driven glove system, Exo-Glove [Fig. 1(a)] [38] was developed. It is an auxiliary glove for the disabled. The assisting force generated by the motor is applied through the cable. Because the system does not have a rigid frame, it is lightweight and easy to wear. However, it is difficult to apply a force at a specific position without a frame, and it is difficult to achieve precise tension control without a tension sensing mechanism process.

Figures 1(b) - (d) show an example of a cable driven frame system with more rigid components than a cable glove configuration. The frame in the cable drive frame system supports the fingers and guides the cable. The cable pulley of HANDEXOS [Fig. 1(b)] is located on both sides of each joint to transmit the generated torque [39]. However, the pulley makes it difficult for adjacent fingers to be sufficiently close, thereby preventing the fingers from moving naturally. The hand exoskeleton system of the PERCRO laboratory [Fig. 1(c)] uses a motorized cable module [40]. In this system, three fingers are used for each finger to change the direction and magnitude of the applied force; however, the overall system is bulky and cumbersome. Cyber Grasp (Fig. 1(d)) is a cable-driven frame system with one motor per finger [41]; in this system, the interference problem is minimized by placing the cable structure on the upper side of the finger. However, due to the components required for the cable mechanism, the system is large.

The hand exoskeleton system, which utilized one active revolute joint for each finger, was developed (Fig. 1 (e)) [42]. It satisfies finger workspaces with a simple structure, but the whole system is quite big due to the space between the hand and exoskeleton structure for finger motions. FESTO developed a hand exoskeleton as a master-slave system with pneumatic actuators (Fig. 1 (f)) [43]. It shows smooth motion, but the required peripherals for the pneumatic actuators restrict its mobility.

In the field of robotics, hand exoskeleton is a widely exploited area by engineers and scientists. Keio University's professionals have developed a mechanism which employs passive clutches to drive a three-finger non-isomorphic hand [44].

A 4 DOF index finger successfully employing master-slave configuration was conceived by believed, he used haptic interface with active and passive multi-point feedback [45]. Stergiopoulos proposed an exoskeleton hand with two fingers having 3 DOF each and a thumb having 4 DOF, which aimed at VR grasping simulations [46]. Italian Institute of Technology (IIT) utilized an optimized RRR un-actuated mechanism to provide 45N of force in their exoskeleton, which can be used for teleoperation, VR and Human- Robot-Interaction (HRI) [47]. Roberto Bortoletto proposes a spring actuated finger exoskeleton (Fig. 2) [48]. A four-fingered, multi phalanx hand was developed by the University of

Wisconsin. Bilal et al propose a bar structured upper limb rehabilitation device based on EEG.

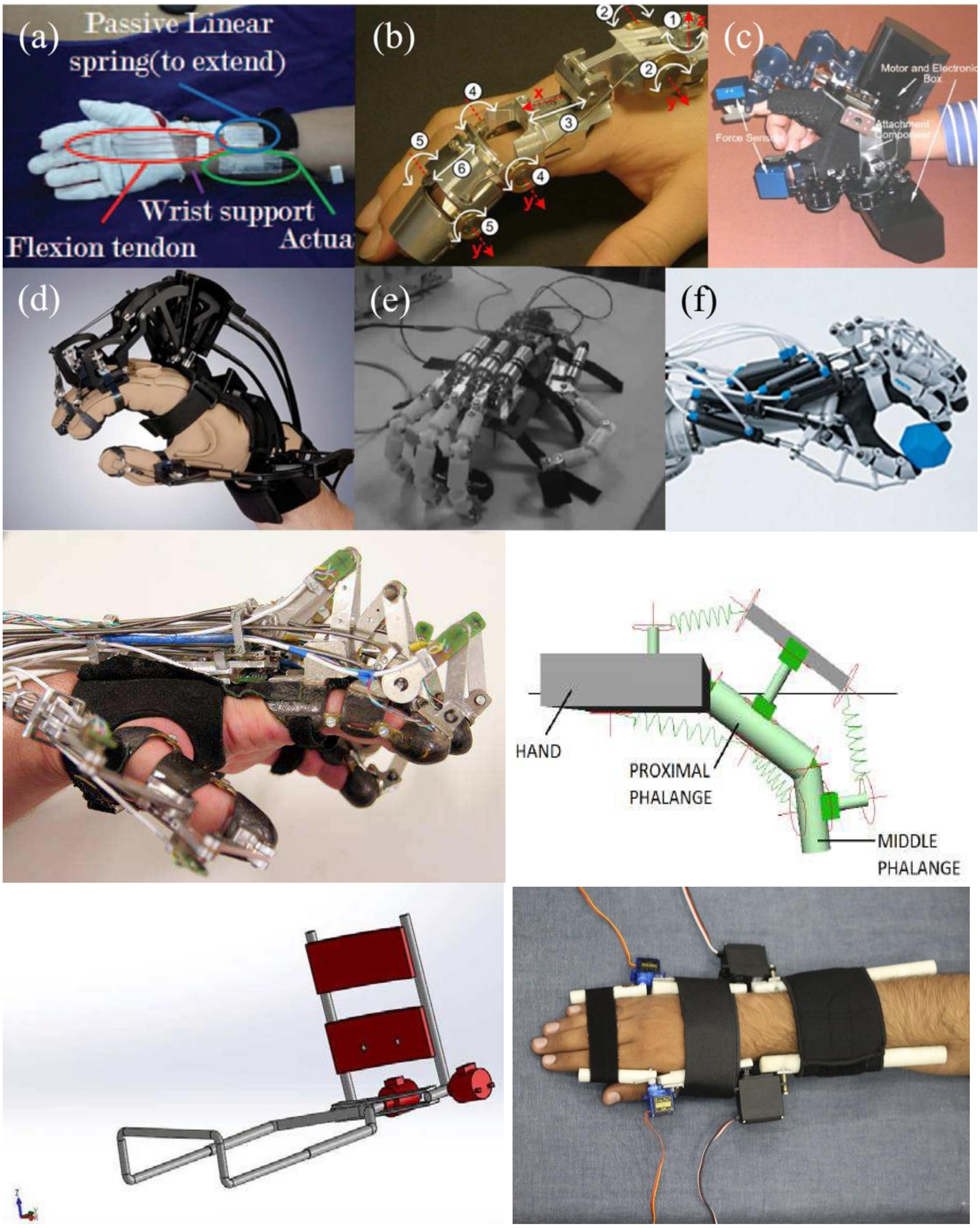


Fig. 2.1 Different devices proposed in the past.

Chapter 3

Methodology

3.1 Methodology

We are proposing a linkage structure exoskeleton for the rehabilitation purpose. For this, we have to calculate the dimensions of the different links of the structure. We also have to find a space combination as well as a mechanism which will help in mimicking the trajectory of the human finger.

Anthropometric data of the human finger and space consideration is taken into account for calculating the dimensions of the various links. Linkage structure comprises 5 links in total and they are arranged in a manner to follow the natural path of the human finger.

This linkage structure will be connected to a wheel assembly which will rotate in a circular path whose center is at PIP. Micro-controller based linear actuators will be used for actuation purpose. Linear actuators provide better control and precision during the motion also, their torque capacity is sufficient enough to execute the extension and flexion of finger.

3.2 Design

The proposed design consists of the following main components:

1. **Linkage Structure**: It consists of 6 links. 3 of the standing links rest on the phalanges of the finger. Two links are somewhat parallel to the palm, these 2 links help

in transmission of motion from the actuator to the link structure. 6th link is in the shape of an arc which moves in a circular path with the center at PIP. This part also rests on a phalange. Linkage structure is so arranged that it should assist the finger in following the natural path of the human finger.

2. **Circular Part**: It supports the wheels which move in a circular path whose center is at PIP. This part act like a connection between the linkage structure and the linear actuator.

3. **Base**: The linear actuator will be mounted on this part, which will move the wheels and thus the linkage structure.

Fig. 3.1 Clockwise from the top: 1. Linkage structure, 2. Base, 3. Circular Part

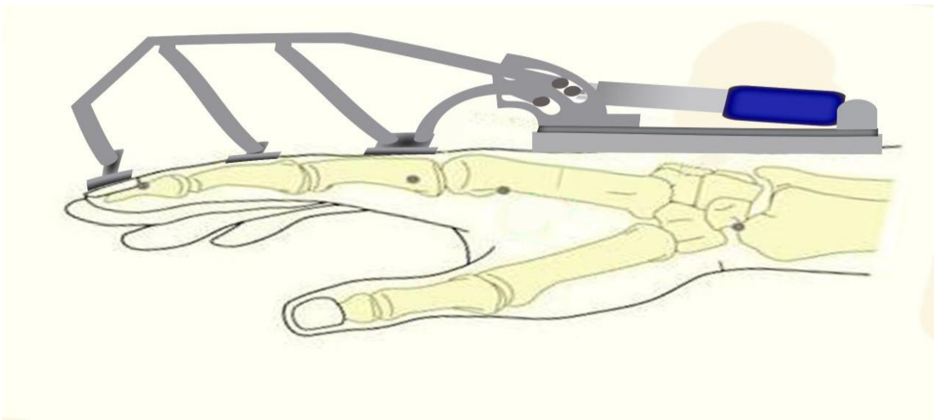


Fig 3.2 Proposed design mounted on Human Hand

3.3 Actuation Mechanism

To impart the force on the device, in order to transfer the motion from this structure to the human finger, a micro controller based linear actuator is employed.

The mechanism of this micro controller based linear actuator is constructed in such a way, that inside a cylinder, a servo motor is enclosed, whose shaft is connected to a lead screw with proper gear arrangement. The gear arrangement converts rotary motion of the servo motor into linear motion of lead screw. The rotation of this motor is controlled by a micro controller.

The advantages of using a micro controller are:

- Better precision and control
- Compatible with the involvement of bio informatic signals like EEG and EMG (in future prospect)

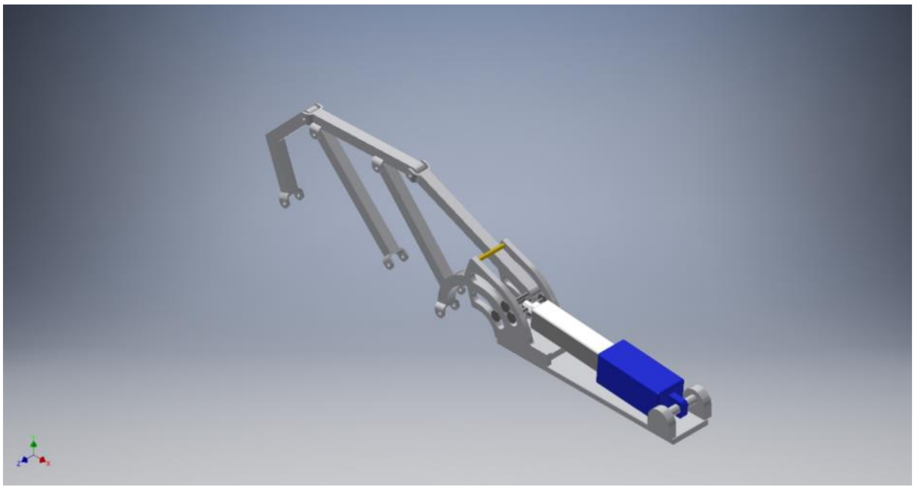


Fig. 3.3 Proposed Design with Actuator

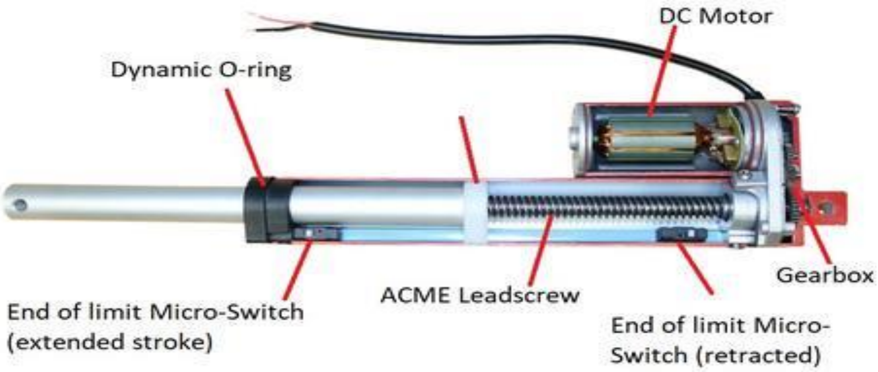


Fig. 3.4 Actuation Mechanism

3.4 Static Simulation

After the designing of the exoskeleton, static simulation was carried out to check the structural strength of the material used. ABS plastic was assigned as a material to the links while aluminum was selected as a material for circular guide way. Simulation was carried out at loading conditions of 30N, using AutoDesk Inventor©.

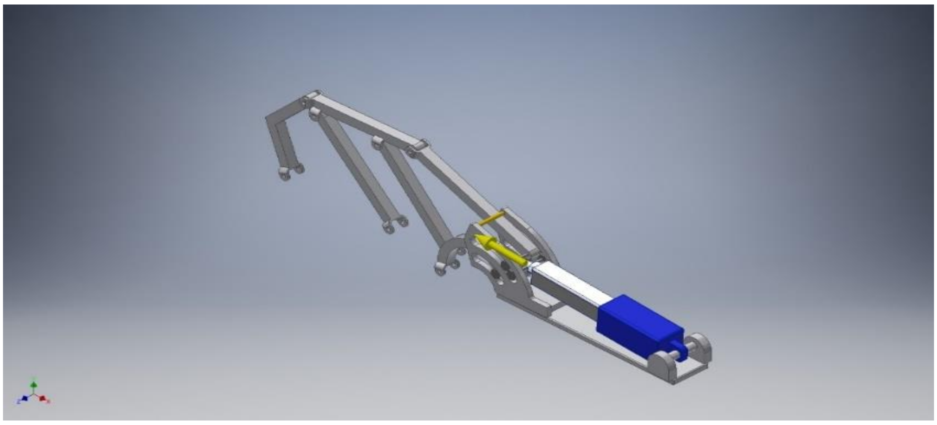


Fig. 3.5 Model with specified load

3.5 Dynamic Simulation

As soon as the structural strength of the material was checked, the dynamic behavior of the device was needed to be analyzed. For this, we conducted dynamic simulation. The following methodology was adopted:

Firstly, we obtained the natural trajectories of the human finger using the software Kinovea©. We marked the phalanges of the finger (index finger) with different colors. Then, we filmed the subject doing flexion exercise (Image 1 & 2). Taking the video as an input, the software generated the trajectory of human finger with respect to the selected origin i.e.: PIP.

Secondly, the corresponding points of the finger assisting device were traced, by carrying out the dynamic simulation on AutoDesk Inventor©. Different positions were obtained at different time instants. Image below shows the trajectory of finger assistive device at a given instant. Comparison between the trajectories obtained by the Kinovea and AutoDesk is shown in the Fig. 3.9. Once we got both the trajectories, i.e. the variation of their traces with time, we plotted all the points on a graph for comparison.

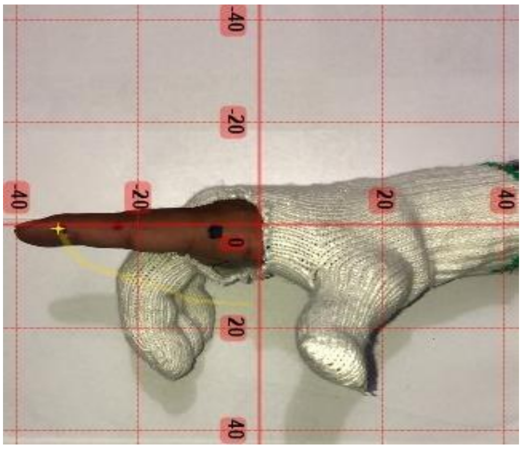


Fig. 3.6 Marked finger in open position

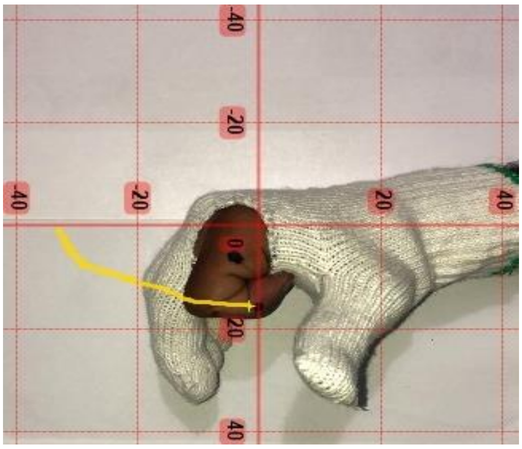


Fig. 3.7 Marked finger in closed position showing trajectory

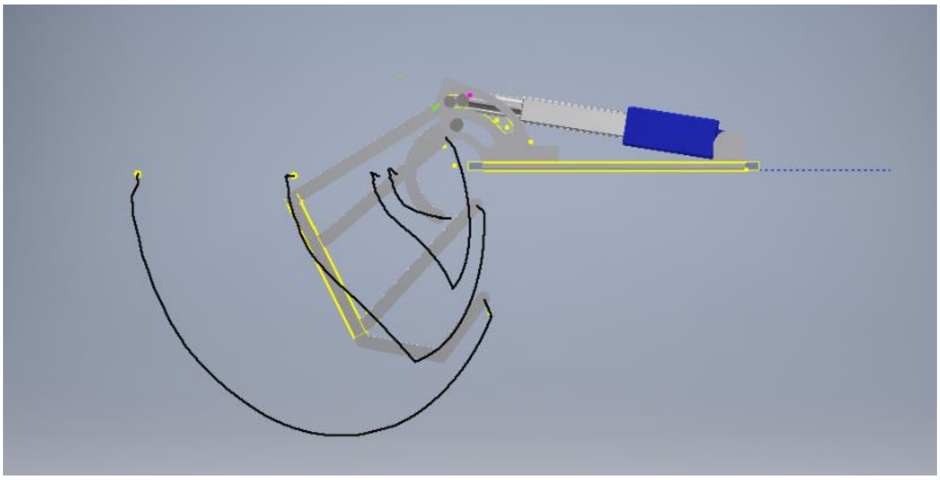


Fig. 3.8 Trajectory of the finger assisting device

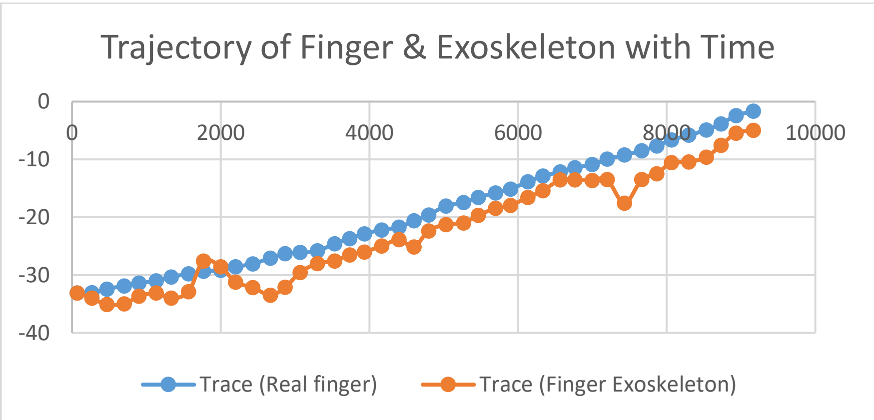
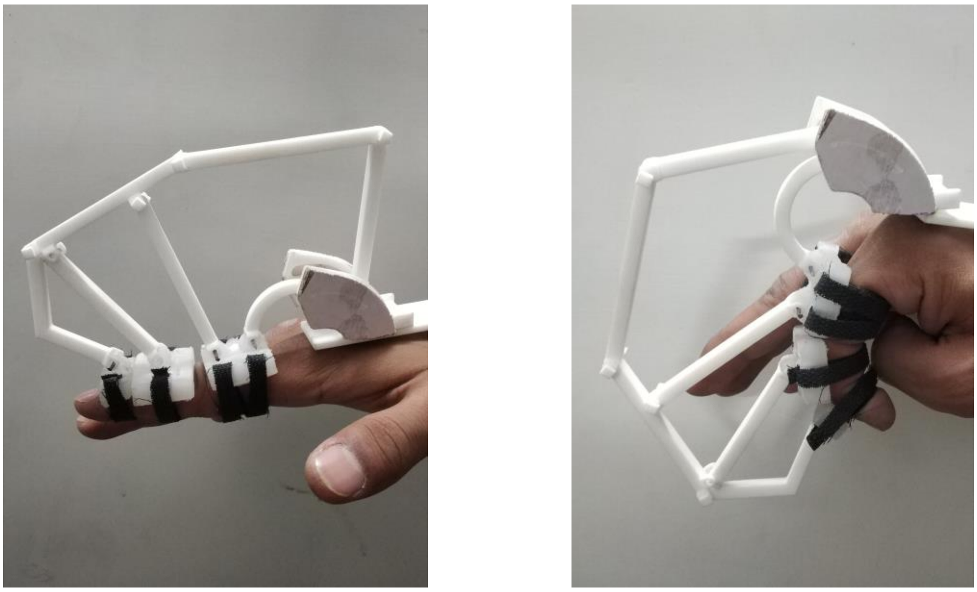


Fig. 3.9 Variation of Human Finger & Exoskeleton with Time

3.6 Manufacturing

For manufacturing of the device, designed under previous sections, we used 3D printing technology. As no facility was available at our department for 3D printing, we approached a New Delhi based firm named Think3D for manufacturing purpose. All the components are manufactured using Selective Laser Sintering (SLS) technique. Material used for manufacturing is ABS plastic.



(a) **(b)**

Fig. 3.10 Manufacured Device mounted on Hand. (a) in relaxed position (b) in flexed position

Chapter 4

Controlling

4.1 Overview of the Brain Computer Interface

The human brain is the most complex organ of the human body and is the central part of the human nervous system. The human brain is the origin of our thoughts and serves as the command center by controlling most of the activities of the human body. The brain is suspended into a fluid known as cerebrospinal fluid (CSF) which helps in absorbing shocks and is protected by the skull and scalp [49]. The brain can be divided into three major parts- cerebrum, cerebellum and brainstem as shown in Fig. 1.

1) Cerebrum: The cerebrum is the largest part of the brain, which contains the cerebral cortex and other structures such as hippocampus, basal ganglia, and olfactory bulb. The cerebrum is the uppermost region of the central nervous system and is regarded as the most important part of the human brain. The cerebrum consists of a huge amount of neurons and each neuron is connected to thousands of other neurons, thus making a large complex network [50]. The cerebrum is associated with brain functions related to thoughts, sensory perception, movements, judgement, emotions and motor functions. The cerebrum is divided into right and left hemispheres and each hemisphere is divided into four lobes: frontal, parietal, occipital and temporal [51].

- **Frontal Lobe** is the largest lobe of the brain and serves as home to the primary motor cortex. The frontal lobe plays an important role in voluntary walking and regulates activities like walking. Other functions involve planning, problem solving, and reasoning.

- **Parietal Lobe** is one of the major lobes of the brain which is positioned above the temporal lobe and behind the frontal lobe. The parietal lobe plays important roles in integrating sensory information from various parts of the body, knowledge of numbers and their relations [52].

- **Occipital Lobe** is known as the visual processing center of the brain. An important functional aspect of the occipital lobe is that it contains the primary visual cortex.

- **Temporal Lobe** consists of structures, which are important for long-term memory. The functions of temporal lobe involve language recognition, memory storage and auditory processing.

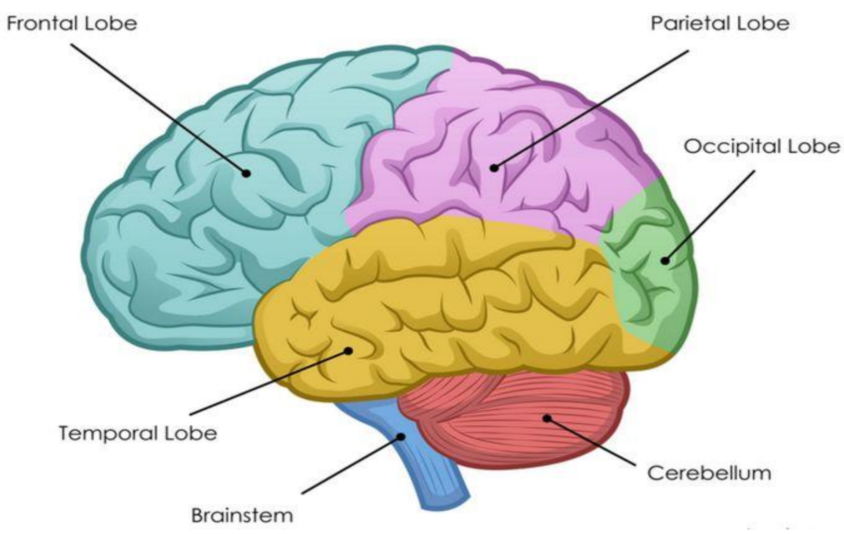


Fig. 4.1 Showing different parts of human brain [53].

2) Cerebellum: The cerebellum is the second largest part of the brain and is found at the lower back of the head. It is also made of two hemispheres. The cerebellum contains about half of the brain's neurons. It is responsible for coordinating motor movements such as balance coordination and posture. It also plays a significant role in cognitive functions.

3) Brainstem: The posterior part of the brain is known as the brainstem and connects the cerebrum to the spinal cord. It plays a significant role in regulating central nervous system and in the regulation of cardiac and respiratory functions. The other functions of the brainstem include regulation of sleep cycle, breathing, eating and heart rate.

4.2 Electroencephalography (EEG)

Electroencephalography (EEG) is a method of recording the brain waves by placing electrodes on the scalp. The term "Electroencephalography" (EEG) is the process of measuring the brain's neural activity as electrical voltage fluctuations along the scalp that results from the current flows in brain's neurons [54]. The first human EEG was recorded by German physiologist and psychiatrist Hans Berger in 1924 [55]. It is an electrophysiological monitoring method of recording electrical activity of the brain. EEG measures the voltage fluctuations produced because of ionic current produced in the brain's neurons. To study brain functions and to diagnose neurological disorders such as epilepsy, dementia, tumor, abnormalities etc., the technique of EEG is widely used.

Routine clinical EEG involves recording of electrical pattern by placing electrodes on the scalp and lasts for about 20-30 minutes. The brain's electrical charge is composed of billions of neurons. The neurons are electrically charged and are in a process of constantly exchanging ions in order to maintain their resting potentials and to propagate action potentials. In this process, the ions of similar nature tend to repel each other and consequently move out of the neurons and pushes other ions, which push their neighbors and thus the process continues making a wave of ions. When this wave of ions reaches the electrodes placed on the scalp, it tends to push or pull the electrons present in the metals of the electrons and as a result, a difference in voltage arises between the electrodes. This recording of voltages over time gives us what is known as EEG. The electric potential because of a single neuron is very small and therefore the EEG activity is the result of the synchronous activity of millions of neurons having the same spatial orientation.

In conventional scalp EEG, recording is typically achieved by placing the electrodes on the scalp with a conductive gel or paste, typically by preparing the scalp area by mild abrasion to reduce the impedance caused by dead skin cells. For most clinical and research applications the names and locations of the electrodes are specified by the International 10–20 system [56]. This is done to maintain consistency across the different laboratories. For clinical applications, the number of recording electrodes used are around 19 but in high-density arrays of electrodes, the number can reach up to 256. The 10–20 system is an internationally recognized method and is based on the relationship between the location of an electrode and the underlying area of the brain. The actual distance between adjacent electrodes is 10% or 20% of the front-rear or left-right distance of the skull and that is why the name 10 and 20. The measurement is taken from the nasion, which is the point between the forehead and the nose, to the inon, which is the bony prominence at the base skull on the midline at the back of the head. Every location consists of a letter to identify the lobe and a number for identifying the location of the hemisphere. The letters F, T, C, P and O stand for Frontal, Temporal, Central, Parietal and Occipital, respectively. Even numbers depict the electrode positions on the right hemisphere, whereas odd numbers correspond to those on the left hemisphere.

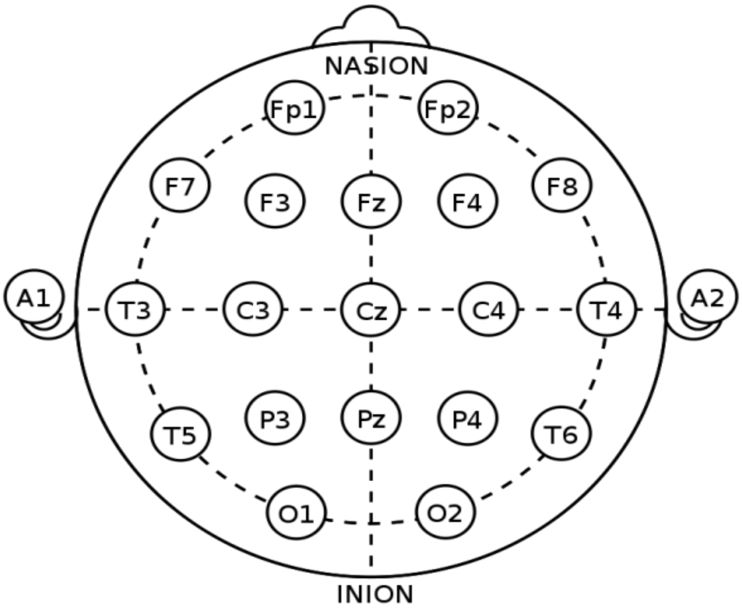


Fig. 4.2 Electrode locations of International 10-20 system for EEG (electroencephalography) recording [56].

The EEG can be typically described in terms of rhythmic activity and these rhythms have distinct properties in terms of spatial and spectral localization.

- Delta rhythm: It lies in the frequency range up to 4 Hz. This is a slow rhythm and is found to be the highest in amplitude. It is seen normally in adults in slow-wave sleep.
- Theta rhythm: It lies in the frequency range from 4 Hz to 7 Hz. Theta is seen normally in young children. It is also observed in drowsiness and in meditation.
- Alpha: found in the frequency range from 7 Hz to 13 Hz. This rhythm is seen in the posterior regions of the head and emerges with closing of the eyes and with relaxation.
- Mu rhythm: These are oscillations in the 8-13 Hz frequency band, being located in the motor and sensorimotor cortex. The amplitude of this rhythm varies when the subject performs movements.

- Beta rhythm: lies in the frequency range from 14 Hz to about 30 Hz. Beta activity is closely linked to motor behavior and is generally attenuated during active movements.
- Gamma rhythm: can be found in the frequency range ranging from 30–100 Hz. It is associated to various cognitive and motor functions.

Table 1. Showing different EEG bands [57]

Band	Frequency (Hz)
Delta	< 4
Theta	4-7
Alpha	8-15
Mu	8-12
Beta	16-31
Gamma	> 32

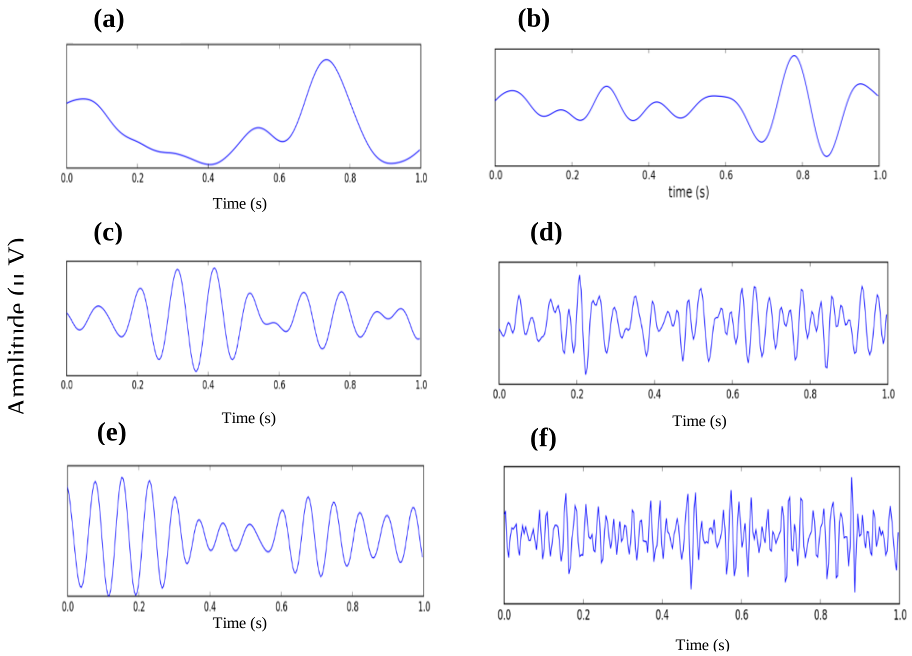


Fig. 4.3 Different brain rhythm as measured by EEG [57], (a) indicates Delta waves, (b) indicates Theta, (c) Alpha, (d) Beta, (e) Mu waves and (f) Gamma

4.3 Data Acquisition

To setup the Brain Computer Interface (BCI) we need an EEG recording data which can be used to run the microcontroller based linear actuator. For this, we decided to record the EEG data at the facility available in Electronics Engineering Department of AMU. The EEG signals were recorded from the 7 conventional EEG recording sites C1, C2, C3, C4, Cz, Fz, Pz. Five subjects volunteered for the recording of EEG signals while performing the following two tasks.

Executed:

Task 1- Initially hand is closed, Subject opens his/her hand and it will be kept open.

Task 2- Initially hand is open, subject closes his/her hand and it will be kept closed.

Due to that small of no. subjects and poor quality of the data recorded in previous step, we decided to utilize a standard data in our study so that better quality results can be achieved.

The standardized data set utilized in this study consists of EEG data collected from one subject with a high spinal cord lesion controlling an EEG/EOG hybrid BNCI to operate a neuro-prosthetic device attached to his paralyzed right upper limb. The cue-based BNCI paradigm consisted of two different tasks, namely the ‘imagination of movement’ of the right hand (class 1) and ‘relaxation/no movement’ (class 2).

A visual signal randomly indicated the user either to close (Green Square) or not to move the device (red square): the two indications were given 24 times each in total separated by inter-trial intervals (ITIs) of 4-6 seconds. Each indication was displayed for 5 seconds after which the device was driven back to open position. Re-setting the exoskeleton into open position required one second.

EEG was recorded from 5 conventional EEG recording sites F4, T8, C4, Cz, and P4 according to the international 10/20 system using an active electrode EEG system

(Acticap® and BrainAmp®, BrainProducts GmbH, Gilching, Germany) with a reference electrode placed at FCz and ground electrode at AFz. EEG was recorded at a sampling rate of 200 Hz, band pass filtered at 0.4-70Hz and pre-processed using a small Laplacian filter.

Fig. 4.4 EEG recording of the subject showing various electrodes while performing MI task.

Fig. 4.5 Experimental Setup of EEG recording.

4.4 Feature Extraction

A feature is a measurable property or characteristic of an observed signal. It should be informative, discriminative and orthogonal to other features. Feature extraction is the method of extracting these features. It can be defined as the process of transforming original data to a dataset with reduced number of variable but with the most discriminative information.

After the wavelet transform, the Daubechies wavelet was used to analyze the channels F4, T8, C4, Cz and P4 of each EEG record. Then the features namely IQR, MAD, variance, skew, kurtosis, energy and standard deviation were calculated. The choice of these particular features can be understood from the Fig. below, which shows that the two classes are statistically different. Particularly, the two classes differ in dispersion and the histogram of class 1appear to be skewed from the normal distribution. Thereby justifying the choice of IQR, MAD, Variance, Standard deviation, Skewness and kurtosis. However, the choice of Energy and MAV was done because it has been reported in many literature that Mu rhythm have lower amplitude than that of the alpha wave.

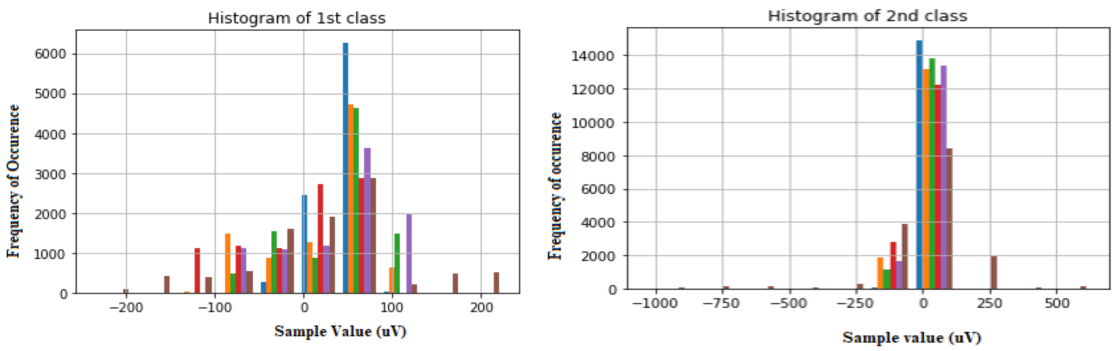


Fig. 4.6 Showing Histogram plots of the two classes.

4.41 Interquartile range (IQR)

IQR is also called the mid-spread or middle 50%, or technically H-spread, is a measure of statistical dispersion, being equal to the difference between 75th and 25th percentiles, or between upper and lower quartiles.

$$IQR = Q3 - Q1 \tag{1}$$

In other words, the IQR is the first quartile subtracted from the third quartile. It is a trimmed estimator and is a commonly used robust measure of scale. The IQR can be used to identify the outliers. From Fig. 4.6, it can be seen that the histogram of class 1 is less dispersed than that of class 2. Therefore, it may capture distinctive information between the two classes.

4.42 Median Absolute Deviation

In statistics, the median absolute deviation (MAD) is a robust measure of the variability and is defined as the median of the absolute deviations from the data's median. MAD is used here to quantify the dispersion between the two classes. In MAD, median is calculated over the absolute values and no higher power term is used, thereby ensuring that all the deviations are weighted linearly. Therefore, making it more reliable than standard deviation.

$$MAD = median(|X_i - median(X)|) \tag{2}$$

4.43 Variance

Variance is the expectation of the squared deviation of a random variable from its mean. It measures how far a set of (random) numbers are spread out from their average value. The variance is the square of the standard deviation, the second central moment of a distribution, and the covariance of the random variable with itself.

$$Var(X) = E[(X - \mu)^2] \tag{3}$$

4.44 Skewness

Skewness is a measure of the asymmetry of the probability distribution of a real-valued random variable about its mean. Skewness is a descriptive statistic that can be used on conjunction with the histogram to characterize the data or distribution.

$$\gamma = E\left[\left(\frac{X - \mathrm{u}}{\sigma}\right)^3\right] \tag{4}$$

4.45 Kurtosis

It is a measure of the "tailedness" of the probability distribution of a real-valued random variable. The kurtosis is the fourth standardized moment. Kurtosis is a descriptor of the shape of a probability distribution.

$$Kurt(X) = E\left[\left(\frac{X-\mathrm{u}}{\sigma}\right)^4\right] \tag{5}$$

4.46 Standard Deviation

Standard Deviation is a measure that is used to quantify the amount of variation or dispersion of a set of data values. A low standard deviation indicates that the data points tend to be close to the mean of the set, while a high standard deviation indicates that the data points are spread out over a wider range of values. The standard deviation of a data set is the square root of its variance.

$$SD = \sqrt{\frac{1}{N}\ \sum_{n=1}^{N}\left(\left(x[n] - \frac{1}{N}\sum_{n=1}^{N} X[n]\right)^2\right)} \tag{6}$$

4.47 Energy

Energy is defined as they are under the squared magnitude of the considered signal. Mathematically,

$$Es = \sum_{n=-\infty}^{\infty} |x(n)|^2 \tag{7}$$

4.48 Mean Absolute Value (MAV)

It is calculated by taking the absolute value of the all the samples and then by calculating the mean of the resultant samples. Mathematically, it can be defined as:

$$MAV = \frac{1}{N}\sum_{i=1}^{N} |x_i(n)|$$

4.5 Feature Selection

This chapter describes the feature selection driven classifier combination approaches for the classification of Motor imagery based EEG. Feature selection, widely used by researchers under different names such as variable selection, attribute selection or variable subset selection. It is the process of selecting a subset of relevant features for the construction of classifier different combined features. Before performing the feature selection, we normally assume that the data contains many redundant or irrelevant features. Redundant features are those, which provide not more information than the currently selected features, and irrelevant features provide no useful information in any context. Feature selection techniques is to be distinguished from feature extraction. Feature extraction creates new features using functions of the original features, whereas feature selection returns a subset of the features. In the real world classification domain the class probability and class conditional probability is often unknown a priori, often the feature suitable for particular classification test is not known in advance. Therefore, randomly features are chosen for classification problem.

Feature selection techniques are used for four reasons:

1. Simplification of different combined features to make them easier to be interpreted [57].
2. Shorter training times,
3. To avoid the curse of dimensionality,

4. Enhanced generalization by reducing overfitting.

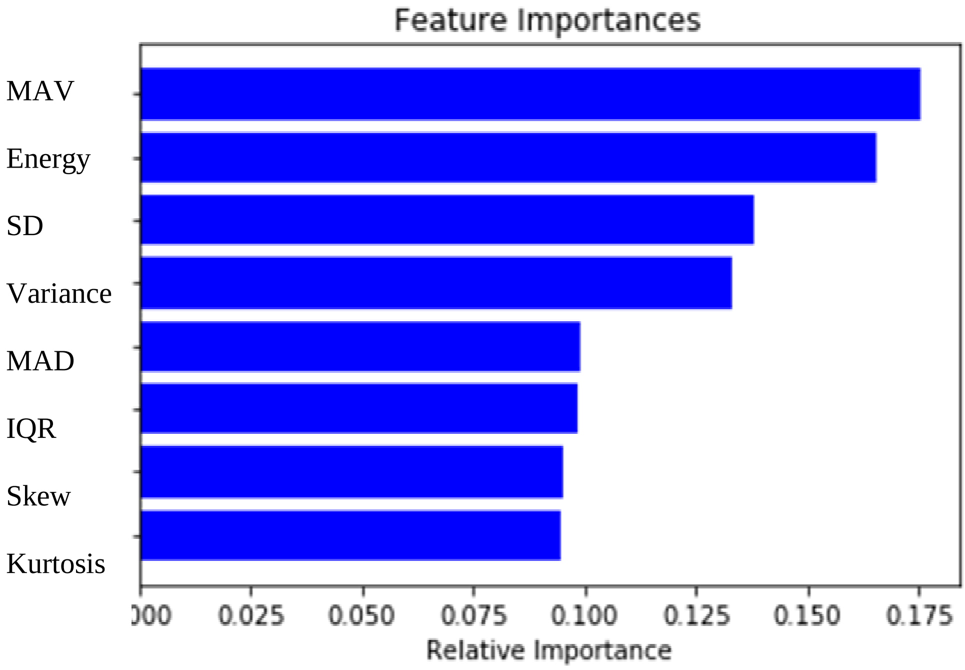


Fig. 4.7 Showing relative feature importance.

In this study, Random forest based feature selection method is used. Random forests consist of few hundred decision trees, each of them built over a random extraction of the observations from the dataset and a random extraction of the features. Not every tree sees all the features or all the observations, and this guarantees that the trees are de-correlated and therefore less prone to over-fitting. Each tree is also a sequence of yes-no questions based on a single or combination of features. At each node (this is at each question), the three divides the dataset into 2 groups, each of them hosting observations that are more similar among themselves and different from the ones in the other group. Therefore, the importance of each feature is derived from how "pure" each of the group is. When training a tree, it is possible to compute how much each feature decreases the impurity. The more a feature decreases the impurity, the more important the feature is. In random forests, the impurity decrease from each feature can be aggregated (majority vote) across trees to determine the final importance of the variable. For classification, the measure of is either Gini impurity or entropy (Information gain).

Table 2. Showing relative feature importance of the features

FEATURE NO. AND NAME	80-20% TRAINING-TEST PARTITION
1	0.09918364
2	0.09468473
3	0.17526146
4	0.13827761
5	0.09495038
6	0.09873715
7	0.16575618
8	0.13314885

The ranked features using random forest are shown in Fig. 4.5. It can be seen that Mean absolute variation (MAV) has the highest feature importance while kurtosis has the lowest. Feature importance indicates the variation capturing power of a feature. This suggests that MAV and entropy should be the best features while skewness and kurtosis should not perform much well in this study.

4.6 Classification

The classification of EEG signals plays an important role in biomedical research. Classifying EEG signals is very important in the diagnosis of brain diseases and for contributing to a better understanding of cognitive processes. It is, firstly, important to extract useful features from raw EEG signals, and then use the extracted features for classification. According to [1] classifiers used in BCI research are generally of 5 types. Linear classifiers, nonlinear classifiers, neural network, nearest neighbor classifiers and a combination of these. Linear classifiers are discriminant algorithms that use linear functions to distinguish classes. These are the most popular algorithms for BCI applications.

Neural network is also a widely used classifier in BCI research. Neural network is an assembly of several artificial neurons, which enable to produce nonlinear decision boundaries. Nonlinear classifiers produce nonlinear decision boundaries, which enable them to perform more efficient rejection of uncertain samples than discriminative classifiers.

In this work, Random Forest algorithm was optimized for classifying EEG signals. Random forests is an ensemble learning algorithm. The basic premise of the algorithm is that building a small decision-tree with few features is a computationally cheap process. If we can build many small, weak decision trees in parallel, we can then combine the trees to form a single, strong learner by averaging or taking the majority vote. In practice, random forests are often found to be the most accurate learning algorithms to date. The pseudocode is illustrated in Algorithm 1.

The algorithm works as follows: for each tree in the forest, we select a bootstrap sample from S where S (i) denotes the ith bootstrap. We then learn a decision-tree using a modified decision-tree learning algorithm. The algorithm is modified as follows: at each node of the tree, instead of examining all possible feature-splits, we randomly select some subset of the features $f \subseteq F$. where F is the set of features. The node then splits on the best feature in f rather than F. In practice, f is much, much smaller than F. Deciding on which feature to split is oftentimes the most computationally expensive aspect of decision tree learning. By narrowing the set of features, we drastically speed up the learning of the tree. The majority voting of the classification trees that have been formed obtains the prediction of the classification.

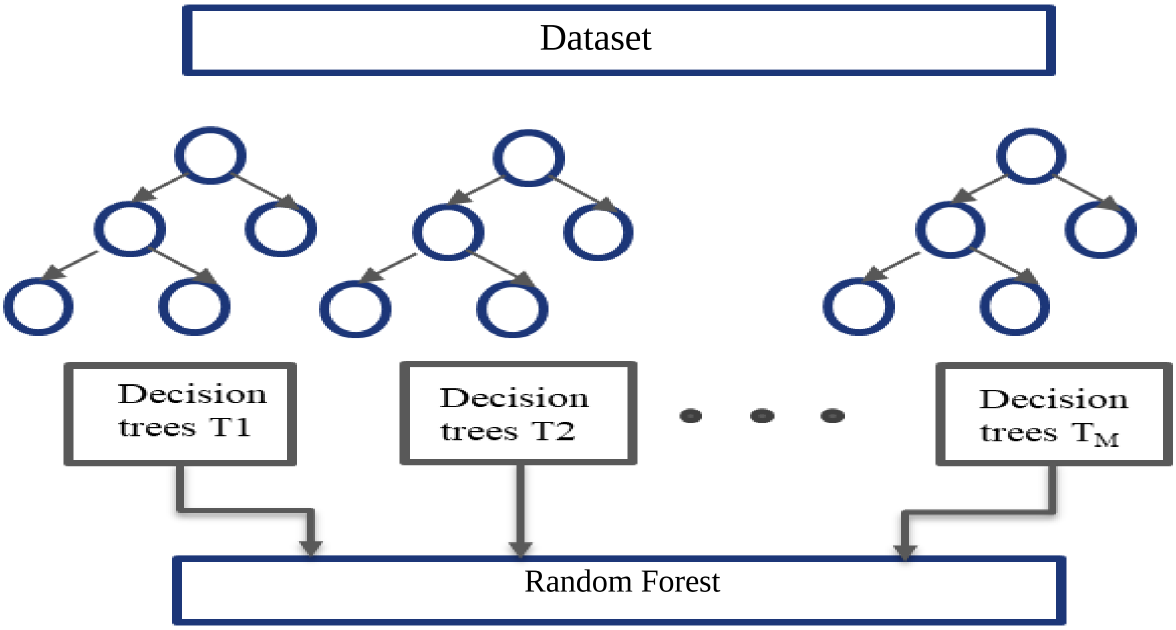


Fig. 4.8 Showing decision tress in a random forest.

Random forest is an extension of a collection of methods developed by Breiman (2001) and is used to improve the classification accuracy. The randomization process in random forest to form the tree is carried out not only on the sample data but also on the predictor variables, leading to a collection of classification trees with different sizes and forms. The expected result is a collection of classification trees with very low correlation between the trees. This low correlation reduces the classification accuracy produced by random forest

Table 3. Pseudo Code for Random Forest algorithm

Algorithm 1 Random Forest

Precondition: A training set S := (x_1, y_1), . . . ,(x_n, y_n), features *F*, and number of trees in forest **B**.

```
function Random_Forest(S, F)
  H←0
  for i ϵ 1, …. , B do
      S(i) ← A bootstrap sample from S
      hi ← RandomizedTreelearn(S(i),F)
       H ←H U {hi}
  end for
  return H
end function

function RandomizedTreelearn(S,F)
    At each node:
        f ← very small subset of F
        Split on best feature in f
    return The learned tree
end function
```

Chapter 5

Results and Discussion

5.1 Results of Static Simulation

The static analysis has reflected an idea of the distribution of various properties over the complete assembly using localized mesh control through finite element analysis. The properties discussed in the static analysis report are:

Stress, Displacement, Strain and Safety Variation.

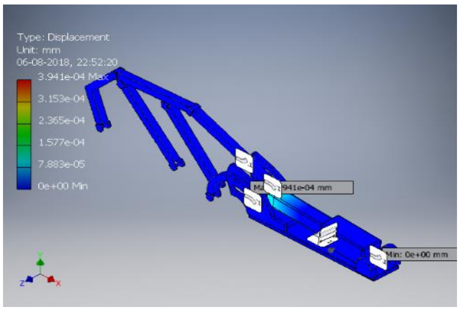


Fig.5.1 Distribution of Stress

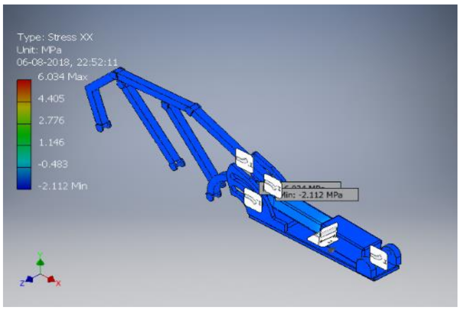


Fig. 5.2 Variation of Displacement

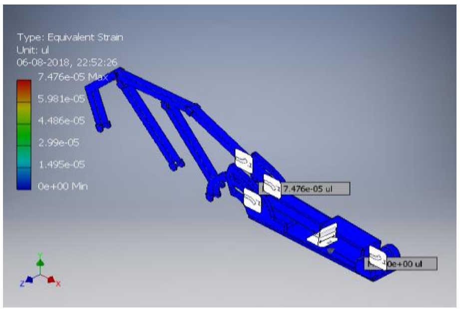


Fig. 5.3 Variation of Strain

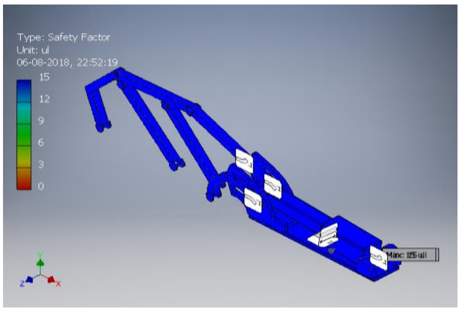


Fig. 5.4 Factor of Safety Variation

5.2 Results of Feature Classification

We have used several measures in order to evaluate the effectiveness of our method. These measures are classification accuracy, sensitivity and specificity.

$$Classification\ accuracy\ (\%) = \frac{TP + TN}{TP+FP+FN+TN}$$

Where, TP is True positive, TN is True negative, FP is False positive, FN is False

Table 4. Showing different combined features and the corresponding selected features

No of Selected Feature	Features
1	F3
2	F3, F4
3	F3, F4, F8
4	F3, F4, F8, F2
5	F3, F4, F8, F2, F7
6	F3, F4, F8, F2, F7, F1
7	F3, F4, F8, F2, F7, F1, F6
8	F3, F4, F8, F2, F7, F1, F5

Table 5. Shows the classification accuracies on the testing data for the different combined features. Among the, #5 and #2 achieved the highest classification accuracy 85.41%

No of Features Selected	Classification Accuracy (%)
1	**62.5**
2	**85.41**
3	**76.14**
4	**63.85**
5	**85.41**
6	**76.97**
7	**78.64**
8	**72.5**

Negative, TN is True negative.

The wavelet transform analysis was performed on the dataset and the feature importance of the different extracted features was calculated using the Random Forest Different combined features in Scikit-learn. After which, the selected features were classified into two classes. Table 4 shows the combination of different features according to their relative importance. Table 5 shows the classification accuracy of those combined features according to the relative importance. Therefore, we constructed eight different combined features with a different number of features to obtain the classification different combined features. In Table 4, F3 is shown to be with the highest feature importance, hence selected first. After which F3 an F4 are combined, then F3, F4 and F8 and so on. From Table 5, it can be seen that though the feature F3 has the highest relative importance among the extracted features, it did not capture the significant distinctive information. However, combining F3 and F4 achieved the highest classification accuracy of this method. This suggests that feature F4 compliments the information captured by F3 and enhanced the accuracy. Similarly, when 5 features are selected it achieved a similar accuracy of 85.41 as reported for 2 features.

Chapter 6

Conclusion and Future scope

In this study, design and development of a linkage structure based exoskeleton for the finger rehabilitation has been proposed. The structural strength of the designed device is laid down by the static simulation results. The results clearly showcased that different design parameters fall well under stipulated limit. This study also proves that the proposed design strongly mimics the natural trajectory of human hand, through dynamic simulation results using Kinovea software.

This study utilized the robotic technology for the controlling of proposed exoskeleton. Microcontroller based linear actuator Firgelli is anticipated to be used for the actuation of designed exoskeleton. For the controlling of this actuator, use of EEG signals is proposed. The EEG data used in the study is analyzed on statistical features like Mean absolute Variation, MAD, skewness, kurtosis, IQR, standard deviation, variance and energy. All these parameters are utilized to extract the underlying information from a dynamic EEG. This study has shown that the proposed features were successful in capturing the relevant distinguishing information. Also, it can be seen that the different combined features #2 and different combined features #5 has the same accuracy while #5 uses 5 features and #2 uses 2 features. This shows that a good accuracy can be observed by using lesser number of features and thereby relieving the computation cost of the method.

The future course of study should aim to program the microcontroller in accordance with the EEG data, so that over all working of device can be carried out. Also, in the near future this approach can be extended to develop various finger assisting devices as per the anthropometric data of different fingers. Connecting all the finger assisting device to a controller will ultimately result in developing a hand rehabilitation device. The individual assistance provided to each finger during the rehabilitation of human finger would be a novel method.

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