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Design and Application of Mind Waves Smart Sensor-Enabled Rehabilitation Gloves

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ABSTRACT
— In an effort to develop more sophisticated and efficient approaches, rehabilitation practices are always changing. The development of Rehabilitation Gloves with Mind Wave sensor, a ground-breaking invention in the field, was the result of this paper's goal to provide a cutting-edge and seamless rehabilitation strategy. These gloves, which use pneumatic technology, give patients in need of rehabilitation exact control over their hand movements. These painstakingly designed gloves provide complete support during the recovery process by combining brainwave neural signals, EMG sensors, and muscle reading sensors. The design concepts and key hardware elements of the glove are examined in detail in this study. Importantly, this breakthrough provides excellent treatment and new hope to stroke survivors and a variety of other people in need of rehabilitation. This proposal's ability to enable patients to receive rehabilitation from the convenience of their homes, doing away with the necessity for trips to rehabilitation facilities, is a noteworthy benefit. This makes the recovery process easier and more effective by reducing the discomfort that comes with typical treatment and cutting down on rehabilitation time. By improving the lives of those in need and opening the door for a more patient-centric approach to care, the Rehabilitation Gloves with Mind Wave mark a substantial advancement in the field of rehabilitation. SolidWorks and MATLAB were used to simulate the system that was described, and laboratory implementation was used to confirm its experimental validity.

DOI :

1 Introduction

A. Background and Motivation

The human hand plays a vital role in facilitating physical interaction and grasping capabilities. Its intricate design, consisting of a palm with five fingers connected to the forearm by the wrist joint, is a marvel of natural engineering [1]. However, hand weakness, resulting from conditions such as stroke, can severely impact the quality of life. Stroke, affecting 15 million individuals worldwide, ranks as the third leading cause of disability and represents a significant health concern, particularly in Western countries. More than 75% of stroke survivors experience upper extremity impairment, often affecting hand and wrist mobility. Although recovery is possible, it varies significantly between individuals based on factors like the type and extent of impairment. Prolonged recovery can limit daily activities, social inclusion, and productivity while imposing economic burdens [2]. As a result, innovative solutions are essential to help survivors regain hand functionality and improve their quality of life.

B. Main Challenges

The development of rehabilitation gloves, though explored in academia and industry, faces several challenges related to safety, efficiency, mechanical systems, human-machine interfaces, performance evaluation, and cost-effectiveness [3]. Designing a rehabilitation glove that offers both safety and freedom of movement is crucial. The intricate biomechanics and anatomy of the human hand need to be carefully considered to prevent injuries or discomfort. Additionally, a portable, lightweight, and cost-effective design is essential for practicality. Advances in robotic devices have made it possible to create smaller, robust components, enhancing the portability of rehabilitation gloves [4]. Additionally, a human-machine interface that accounts for the intelligence in exoskeleton control represents a distinct challenge. Control design for rehabilitation gloves significantly differs from traditional robotic control. It must align with the user's movement intentions while ensuring the safety and efficiency of the device. This "human in the loop" system requires precise control over the glove's actions [5].

Evaluating device performance poses challenges due to limited access to clinical settings and the need for specialized training. Testing is often conducted in controlled laboratory conditions or through software simulations, offering cost-effective alternatives. The high cost of developing rehabilitation gloves is another challenge, as advanced technology is associated with specialized hardware, materials, and extensive testing, often limiting the target market's affordability [6].

C. Importance of Rehabilitation after Stroke Recovery

Post-stroke rehabilitation plays a pivotal role in the recovery process. It aims to help survivors regain lost skills and abilities by offering specialized programs tailored to individual needs. The interdisciplinary rehabilitation team, including professionals from various fields, collaborates to address the consequences of stroke, enhance cognitive and physical functions, and support daily living [7].

D. Reviews

Emerging technological innovations, notably in the realm of rehabilitation robotics, present considerable promise in assisting the recovery of impaired upper limbs through the implementation of repetitive and task-specific therapeutic protocols [8]. A substantial body of literature, spanning multiple reviews, has demonstrated positive outcomes in the restoration of upper limb motor function when employing robotic rehabilitation devices as part of the treatment regimen. Escalating demand for rehabilitation robotics and alternative therapeutic strategies has arisen due to resource constraints in healthcare, exacerbated by the imperative to reduce hospitalization durations for economic reasons [9]. Consequently, the role of robotic devices in the field of rehabilitation research has become pivotal in addressing the rehabilitative requirements of stroke-afflicted individuals. Moreover, the compounding global aging demographic and the increasing incidence of stroke cases underscore the growing need for these devices, with a specific focus on facilitating the recovery of arm and hand motor functions. Robotic systems distinguished by precision and reproducibility in their movements are poised to meet these demands by delivering intervention therapy aligned with the prescribed criteria of physiotherapists [10].

A fundamental therapeutic approach in the context of ameliorating impaired motor skills revolves around task-oriented, repetitive movements designed to facilitate the restoration of functionality in patients. Robotic devices play a pivotal role by assisting clinicians in guiding patients through prescribed movements, thereby stimulating neuronal reorganization and the establishment of new connections in the brain a phenomenon known as neuroplasticity. This, in turn, holds the potential to lead to motor recovery [11].

The techniques employed by these robotic systems mirror the approaches used by physiotherapists, enabling them to administer hand rehabilitation in both passive and semi-active modes. Passive treatments involve the robotic device serving as the primary driving force responsible for moving an individual's fingers [12]. Conversely, semi-active therapy encourages the active involvement of an individual's own fingers and hand, with the robot providing supplementary assistance. Consequently, treatments can be structured to emulate the methods employed by physiotherapists, either by directly manipulating the motion of the fingers and hand or by serving as a guiding influence [13].

In addition to facilitating repetitive movements, robotics technology facilitates the collection of quantifiable data, allowing for the continuous monitoring of a patient's performance. This capability aids both physiotherapists and patients in monitoring subtle changes and improvements in quantifiable indicators of progress, overall treatment outcomes, and the efficiency of the rehabilitation process [13].

The evolution of robotic systems within rehabilitation settings has followed diverse paths. Initial clinical investigations in the field of rehabilitation robotics, exemplified by the MIT-MANUS robotic arm developed at MIT, primarily focused on assessing the effectiveness of target-based robotic-assisted movements [14]. However, many studies emphasized upper limb post-stroke rehabilitation, particularly targeting the shoulder and elbow joints, while neglecting the equally vital hand and finger joints. This oversight had repercussions, as some therapeutic exercises for these devices omitted the essential finger motions needed for pinch and grasp functionalities, prerequisites for regaining the ability to perform everyday activities independently.

The imperative for specialized hand rehabilitation led to the development of various robotic systems in recent years, broadly categorized into two principal types: exoskeletons and end effectors. Exoskeleton-type systems are affixed directly to or worn by patients, enabling them to control the motion [12]. Prominent examples include the Hand-Wrist Assisting Robotic Device (HWARD) and PMHand, as well as the emerging category of soft robots, crafted from pliable materials, rendering them less complex, safer, more portable, and flexible [15].

M. R. Mercier et al., Conducted a meta-analysis comparing the efficacy of exoskeleton and end-effector, robot therapies for the recovery of finger-hand motor function in stroke survivors [17]. In addition, comprehensive reviews [18] assessed the status of research in hand rehabilitation robotic technology, evaluating several devices to provide insights into the current state of the art.

Exoskeleton devices offer patients both active and passive rehabilitation through diverse actuation sources and mechanisms. These mechanisms govern how power generated by actuators is transmitted to drive finger motions. Actuation methods encompass electromotor, hydraulic, and pneumatic systems, with electromotors being the preferred choice due to their reliability, ease of installation, and high precision. In contrast, hydraulic and pneumatic actuators are less commonly employed due to challenges such as noise, leakage, control issues, and the need to manage compressed air and fluid. These methods necessitate multiple components, including compressors, various valves, regulators, pumps, and control elements, which introduce complexity and cost to the design and control of rehabilitation devices [12].

The primary function of the actuation mechanism is to translate the motion from actuators to the fingers to execute hand therapy exercises [12]. The specifics of this process vary depending on the nature of the actuator and can be categorized into key classifications: pneumatic actuation, linkage-based actuation, cable-driven systems, and gear-motor actuation. While linkage and gear-motor actuation are prevalent in hand rehabilitation devices, they often involve rigid linkages, pulleys, gears, and mechanisms, leading to the development of bulky, complex, and costly exoskeleton hand devices [12]. These devices can be uncomfortable for users and may have limited workspace coverage. This, in turn, affects the biomimetic characteristics of these devices and can result in misalignment with the anatomical axis of finger movements. Conversely, soft exoskeleton hand rehabilitation devices provide a lightweight, non-rigid alternative but are primarily actuated by pneumatic systems, which require complex components and control systems while offering limited accuracy [13].

Cable-driven mechanisms have also found frequent application in hand rehabilitation robots, with some systems employing soft gloves and cable-driven mechanisms [13]. Notable examples include the Exo-Glove, handcar, and Gloreha. Cable-driven systems offer a lighter, more comfortable, cost-effective, and portable alternative, enabling the placement of motors and sensors away from the hand device or glove attachment.

E. Contribution

The proposed design approach tackled some of the issues outlined in existing literature. It centered on the development of a hand rehabilitation device featuring a flexible structure accommodating various hand, finger, and thumb sizes. It incorporated a lightweight and secure link to the actuation and sensing system, strategically positioned away from the palmar side of the hand to ensure unimpeded interaction with real-world objects. This design choice was informed by consultations with physiotherapists, aiming to provide users with the freedom to engage in training involving repetitive motion patterns with real objects. The proposed device offered training for functional tasks, with the five fingers moving collectively in a reaching motion. In contrast to most other systems in the literature that actuated each finger independently, the current approach simplified actuation, sensing, and control complexity by utilizing only two motors instead of five.

Furthermore, the proposed hand device boasted a lightweight design, with the entire hand attachment weighing in at 246 grams. This portability sets it apart from many other devices documented in the literature, enhancing patient comfort and ease of use. These features effectively reduced the overall complexity and cost of the proposed device, differentiating it from most systems described in the literature. This paper presents the analysis of a preliminary study that evaluated the device's accessibility, reliability, and user comfort, focusing on healthy adults. These critical factors would impact the acceptance and effectiveness of the device for stroke patients.

This paper begins with the model and control of the upper limb for hand impairment based on forearm EMG signals and brain signals. Hierarchical control with user movement intent is proposed to help people with hand disabilities perform finger pinching and hand gripping in different wrist positions. It includes experimental work by collecting EMG data and simulation for theoretical work, tuning, design, and performance verification. So, it offers several key contributions as the following:

- Development of a rehabilitation glove with fully activated fingers and a wrist design in a simulated environment based on Mind Wave Smart Sensors.
- Establishment of relationships between forearm EMG signals, finger pinching, hand gripping forces, and different wrist positions to predict hand grip forces and angles based on EMG signals.
- Evaluation and validation of the overall system performance.

2. Materials

A. The Human Hand Structure

In a broad anatomical context, the human upper limb comprises four distinct segments: the shoulder, arm, forearm, and hand. These segments are characterized by their unique mobility and grasping/manipulation capabilities.

The hand, a pivotal component, is composed of five fingers: the index, middle, ring, and pinky fingers, along with the thumb, as well as the palm, back of the hand, and wrist. Within the human hand's skeletal structure, there exist 27 bones, categorically grouped into three clusters, as shown in Figure 1. Firstly, the wrist is formed by a set of eight carpal bones. Secondly, the root of the hand consists of five metacarpal bones. Lastly, the fingers are comprised of 14 phalanges, further subdivided into three bony components: the distal, middle, and proximal phalanges [15].

The distal phalanx is located at the fingertip and connects to the proximal phalanx situated at the base of the finger through an intermediate phalanx. Furthermore, the proximal phalanges are interconnected with the metacarpal bones within the palm region. Anatomically, the phalanges are linked by specific finger joints, namely the metacarpophalangeal joints (MCP), proximal joints (PIP), and distal joints (DIP) [20].

In terms of mobility, the MCP joint within the hand exhibits two degrees of freedom (DOF), enabling adduction/abduction and flexion/extension movements. Conversely, both the PIP and DIP joints are characterized by a single DOF, facilitating flexion and extension motions. It's important to note that the interplay between the PIP and DIP joints is interdependent, as the DIP joint operates as a rotation driven negative DOF within the PIP. Consequently, each individual finger can be conceptualized as a 4 DOF mechanism, featuring three active joints and one passive joint [15].

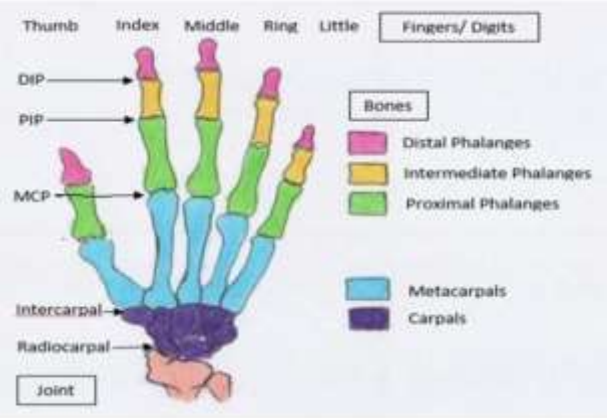


Figure “1” Sketch for bones and joints of a human hand.

B. External hand designs using SolidWorks

The initial design of the exoskeleton hand was executed using the tools provided by SolidWorks, a robust 3D modeling software. SolidWorks streamlines the process of creating 3D product designs by initially drawing in 2D profiles, which are then elevated to a 3D format to yield a coherent and solid configuration. While a multitude of computer-aided design (CAD) software options are available, each serving design needs, we opted for SolidWorks over other alternatives. Its appeal lies in its capacity to employ a parametric feature-based methodology in part modeling, enabling design alterations at any phase of the design process. Additionally, it seamlessly integrates with Sim Mechanics in MATLAB, contributing to its selection.

In devising the hand model, we adhered to fundamental design criteria aimed at achieving an exoskeleton hand design that closely emulates the natural human hand.

Initially, we established the anatomical and biomechanical capabilities of the human hand. The resulting design, as depicted in Figure 2, comprises five fingers intricately articulated to yield the correct number of degrees of freedom (DOF); a total of 15 DOF, with 14 DOF distributed among the fingers.

Our design closely mirrors the bone structure of the human hand, albeit with exceptions in the palm and wrist regions. Each of the index, middle, ring, and pinky fingers is structured into three distinct segments: the proximal, middle, and distal phalanges. The thumb, however, consists of only two segments: the proximal and distal phalanges. Notably, the palm is fashioned without the metatarsal shaft, rendering it stationary, while the wrist is configured sans the carpal bones, facilitating flexion and extension movements.

The dimensions and specifications of the exoskeleton hand are outlined in Table 1. We have made allowances for slight tolerances in each link, ensuring adequate space for future additions, such as additional comfort materials that may enhance wearability. The selected dimensions were chosen to encompass a range that accommodates the hand measurements of both Asian and American women, considering the paucity of dimension-specific data in the existing Literature.

a)

b)

Figure “2” a) The exoskeleton hand in SolidWorks, b) The exoskeleton finger.

TABLE 1 THE DIMENSIONS AND SPECIFICATIONS OF THE EXOSKELETON HAND

Hand measurements

Hand length	19				
Hand width	7.5 / 9.5 (with the thumb)				
Hand depth	3.5				
Wrist breadth	6				
	Digit 1	**Digit 2**	**Digit 3**	**Digit 4**	**Digit 5**
Distal phalanx link length	2.5	2.5	2.5	2.5	2
Intermediate phalanx link length	-	2.5	2.8	2.5	2
Proximal phalanx link length	3	4	4	4	3
Tip finger crotch length	5.5	9	9.3	9	7
Tip to wrist length	11.5	16.5	19	19	17
Distal interphalangeal breadth	-	1.7	1.7	1.7	1.7
Proximal interphalangeal breadth	-	2	2	2	2
Interphalangeal breadth	2	-	-	-	-

Legend:
The units for all measurements are in centimeters (cm).
The (-) indicates that data is relevant to the digit.
The numbering of the digits is 1 to 5, representing the thumb, index, middle, ring, and pinky fingers, respectively.

C. Stress analysis

Efforts have been directed toward ensuring that the hand model that has been created can effectively engage in and support hand movements. Moreover, the design of the fingers is such that they replicate the spatial path closely resembling that of natural fingers during typical grasping actions. Furthermore, the inherent range of motion and the distribution of force along the limb when interacting with objects have been accounted. An additional crucial aspect of our hand design is that it allows for direct manipulation at each joint to mimic the actual human hand performance. This approach mitigates issues related to stiffness and, more notably, the challenges associated with accurately tracing the path of each finger during hand movement. To enhance the system's representation, certain assumptions in defining the external hand model of the exoskeleton have been defined as:

- All joints (including DIP, PIP, and MCP connections) possess a single degree of freedom (1 DOF), primarily enabling flexion and extension movements.
- For each finger, we've based the joint angles (DIP, PIP, and MCP joints) on a rectangular body power grip with a grip diameter of 25 cm, akin to a dynamometer's diameter.
- In scenarios involving finger pinching, force application is concentrating on the medial core of the distal phalanx, treating all external forces as a unified entity.
- All common actuators receive force inputs and generate angle outputs, observing to control theory principles.

Despite diligent attention to scaling in the design of the exoskeleton hand, challenges related to the kinematic alignment between the exoskeleton and the human hand pose difficulties in seamlessly attaching the exoskeleton to the human hand. Figure 3 shows the results of the stress analysis of the designed exoskeleton hand in SolidWorks.

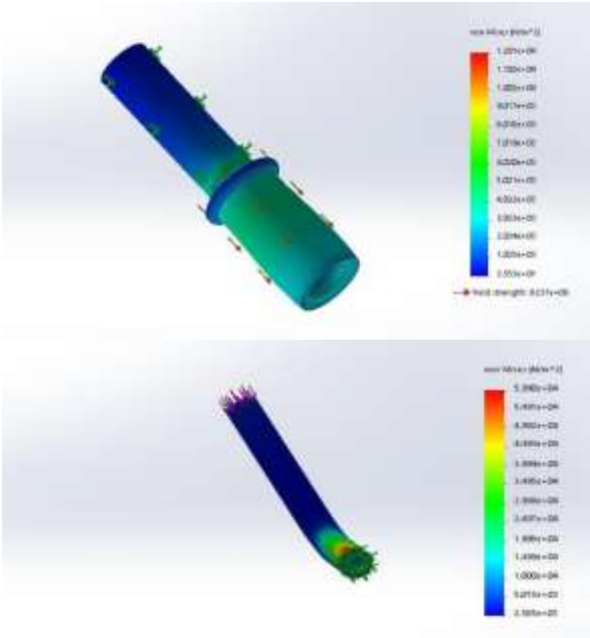


Figure “3” Stress analysis of the designed exoskeleton hand in SolidWorks.

2.1 Air Pump Varieties

An air pump serves the purpose of pushing air, encompassing diverse applications such as aerating aquariums, powering pneumatic tools, and even contributing to the functioning of a pipe organ. Various types of air pumps exist, each equipped with components like vanes, pistons, impellers, or diaphragms that drive the airflow by creating areas of low pressure that subsequently fill with more air.
While pumps and compressors share similar mechanisms, they operate in different fluid

regimes, leading to distinctions in terminology:

- Compressors deal with compressible fluids, typically gases, while pumps operate on typically incompressible fluids like liquids.
- Compressors aim for high-pressure rise in closed systems, whereas pumps generate relatively lower pressure in free-flowing systems with minimal backpressure.
- Pumps often function in continuous-flow operations, while compressors may operate intermittently, especially lower-end models.
- Compressors generally incorporate a feedback sensor for pressure control, while pumps operate across their performance curve without adaptive feedback.

A. Enhancements to Human Life

The invention of the air pump has had a profound impact, leading to the creation of vacuum pumps and vacuum tubes, triggering advancements in various domains. Vacuum pumps play pivotal roles in manufacturing light bulbs, the freeze-drying process in medical, food, and biological industries, as well as the atomic energy sector. The advent of compressed air facilitated the development of powerful pneumatic tools, fostering the growth of large cities through construction processes and contributing to the construction of significant structures such as skyscrapers, hotels, and stadiums. Furthermore, reciprocating pumps played a crucial role in the creation of engines, enabling the use of automobiles.

HVAC systems, crucial for maintaining indoor air quality and comfort, are highlighted as essential components contributing significantly to the economy and our daily lives.

B. MICRO AIR PUMP

The details of the employed air pump of MICRO AIR PUMP 370-A (6V) can be written as the following:

- Voltage: DC 6V
- Current: 400mA
- Pressure: 100KPa
- Negative force: -60KPa
- Flow: 3.2L/minute (gas flow)
- Weight: 62 grams
- Cable length: 10cm

Figure “3” Stress analysis of the designed exoskeleton hand in SolidWorks.

2.2 Electromyography (EMG)

A. Collection of EMG data

The process of data collection is initiated by identifying the forearm muscles responsible for various hand movements. An in-depth study of the human hand's anatomy is conducted to pinpoint the specific muscles and their locations, and the procedural details are documented to precisely identify these muscles for inclusion in the experimental procedure documentation. Once the muscle selections are finalized, the experimental setup is conducted before commencing the actual data collection procedure [12].

Eight subjects, randomly chosen from both genders within the age range of 30-40 years, are involved in data collection. Selected subjects exhibit no neuromuscular issues and are briefed, either verbally or through visual aids such as recorded videos. Informed consent is obtained prior to the study. The inclusion of healthy subjects aims to generalize findings for individual differences, aiding in the design, testing, and validation of the proposed control framework.

Muscle weakness in stroke survivors is often attributed to disruptions in the corticospinal tract and muscle atrophy. EMG features collected from stroke survivors exhibit interindividual differences stemming from disturbed motor control, necessitating individualized examination and analysis. Limited access to stroke survivors poses challenges and may impede research progress.

B. Muscle Selection Procedures

The coordinated action of extrinsic and intrinsic muscles contributes to the hand's dexterous movement. Extrinsic muscles originate from the arm and forearm, while intrinsic muscles are entirely within the hand [17]. To establish the relationship between forearm EMG signals and hand grip strength/knuckle and wrist angles, EMG data are collected from muscles displaying higher levels of muscular activity during isometric contractions. Muscles exhibiting superior performance during such contractions are prioritized over those with lower performance.

Forearm muscles coordinating hand gripping are also involved in finger and wrist flexion and extension. Flexor muscles facilitate finger flexion toward the palm and/or wrist flexion toward the front of the forearm, located in the posterior and anterior compartments, respectively. Seven potential muscles are selected based on their actions for the intended tests. Among these muscles, five extrinsic muscles play a role in the flexion and extension of the four medial fingers and the thumb, while an additional two muscles are responsible for wrist movements.

In a broader context, estimating muscle excitation involves analyzing the amplitude of the generated EMG signals. To sustain or enhance pinching/gripping forces, a higher number of motor units and increased firing rates are required. Enhancements in the quality and accuracy of collected EMG signals were achieved by ensuring precise electrode placement for each muscle involved in specific movements. Subjects were directed to undergo several tests to pinpoint the correct location for each muscle, contributing to the refinement of the data collection process.

C. Experiment Set-up

After the completion of the muscle selection procedure, a pre-task protocol is implemented to record general information about each subject, including weight, height, age, and hand length. Subsequently, subjects are seated in an armchair, with their forearms supported and fixed in a single position to mitigate the impact of varied limb movements on the generated EMG signals. The concurrent measurement of muscle excitation and finger pinch force is conducted using multi-channel EMG sensors and a Vernier hand dynamometer (HD-BTA).

The hand dynamometer functions as a strain gauge-based isometric force sensor, amplifying handgrip force applied to its pressure pads and converting it into a corresponding voltage value. The experimental setup relies on the surface EMG technique, ensuring noninvasive muscle activity measurement without involving extensive medical procedures. Electrodes are positioned on the skin without penetrating its surface, distinguishing it from needle electromyography and making it particularly suitable for home-based assistive and rehabilitative devices.

Before electrode placement, the skin areas are scrubbed with a paper towel to eliminate skin oil and moisture, with detailed skin preparation only performed if deemed necessary. Kendall 5400 Diagnostic Tab Electrodes are utilized for data collection, designed specifically for various diagnostic applications. Extensive skin preparation is unnecessary, given that the electrodes feature:

- Conductive adhesive hydrogel for firm adhesion, repositionability, low impedance, and minimal adhesive residue.
- Different adhesive levels to accommodate various skin types, applications, and monitoring situations.
- Laminated Carbon Vinyl for conformability to the skin, torsion relief, and radiolucency.
- Silver/Silver Chloride (Ag/AgCl) sensing element to facilitate electrode defibrillation recovery.

The electrode patches are placed on the chosen forearm muscle of the subject's dominant hand and connected to the LabQuest Mini Data Acquisition through interwires (3 channels; red, green, and black wires with alligator clips). The red (positive) crocodile clip is attached to the electrode patch measuring muscle activation, while the green (negative) crocodile clip is connected to another electrode patch on the same muscle, maintaining a 24 mm spacing between electrodes. A black (reference) alligator clip is attached to an electrode patch near the bone. Subsequently, the manual dynamometer is linked to the LabQuest Miniature data acquisition device, which is connected to a battery-powered laptop. Finally, Logger Lite is launched for manual dynamometer calibration and data logging, with a sampling rate of 2 kHz (2000 data values collected in 10 seconds). Figure5 illustrates electrodes muscle connections.

D. Sensors and devices

Arduino, employing straightforward code, can effectively control and interface with a diverse range of sensors, including those for light, temperature, inclination, pressure, acceleration, and humidity.

Shields: These are pre-assembled circuit boards compatible with Arduino, providing it with capabilities such as engine control, web interfacing, cellular or wireless communication, and the ability to regulate various other devices, as shown in Figure 6.

Figure “4” Electrodes muscle connections

Figure “5” EMG Sensor Board

EMG Muscular Signal Sensor: The EMG Muscular Signal Sensor is a device designed to measure muscle activation in individuals. It gauges the electrical activity of muscle groups both at rest and during contraction. In medical research, precise measurement of muscle activity, contraction, and expansion is crucial. The EMG muscle sensor precisely measures muscle activity and generates a signal reflecting the degree of expansion and contraction.

EMG Muscular Signal Sensor Features: In therapeutic research, where understanding muscle movement, contraction, and extension is vital, the EMG muscle sensor stands as a significant tool. The sensor measures muscle activity, producing a signal that indicates the extent of movement and compression. The output is dependent on the amount of activity within the targeted muscle. Three electrodes in green, red, and yellow connect to the module, transmitting electrical signals generated by muscle movement. Its features can be summarized as a compact Form Factor, Specifically Designed for Microcontrollers and Adjustable Gain through an onboard potentiometer. Moreover, it can be used in many applications, such as Video Games, Robotics, and Medical Equipment.

E. EMG Muscular Signal Sensor Configuration:

The EMG Muscular Signal Sensor module is equipped with five pins as Vs+: Positive control supply, GND-BAT: Ground, Vs-: Negative control supply, SIG: Analog output, GND: Ground. While the required Materials can be determined as, EMG Muscular Signal

Sensor, Male to Female jumper wire. The software of Arduino IDE has been used.

Interfacing the EMG Muscular Signal Sensor with Arduino can be achieved as follows: Ensure optimal functionality by paying attention to proper positioning, Green Electrode: Strategically position this electrode for effective use, Red Electrode: Place this electrode at the end of the targeted muscle, and Yellow Electrode: Situate the last electrode in a location near the desired muscle.

To generate a positive voltage (+Vs), two power supplies or batteries are employed. Initially, we connect the negative side of the first battery to the positive side of the second battery, creating an electrical ground for the power supply, as depicted below.

In this configuration, the positive side of the first battery serves as +Vs, while the negative end of the second battery functions as the ground (Vs). The subsequent circuit diagram illustrates the correct connection of the Arduino to the EMG sensor.

F. Circuit configuration

The circuit configuration of the experimental setup is shown in Figure 7. The configuration includes Battery, Arduino, electrodes, and EMG Sensor Board.

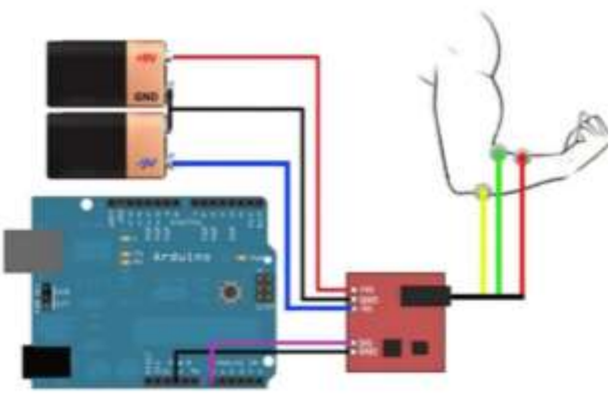


Figure “3” The whole circuit connection

G. Results of EMG Muscular Signal Sensor

The variations in the analog output signal of the module corresponding to the expansion and contraction of the forearm muscle have been monitored. To achieve this, open the Serial Plotter and visualize the output signal. The observed signal has been dissipated in Figure 8 using serial Plotter.

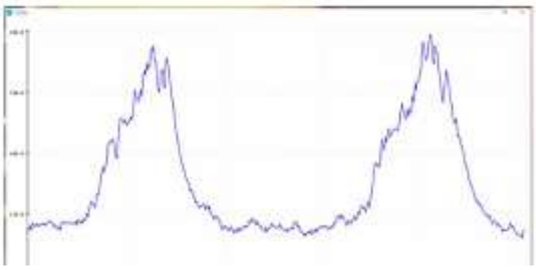


Figure “7” The observed signal using the serial Plotter

H. Processing of the Forearm Electromyogram Signals

The control method based on electromyography (EMG) architecture can be classified into either pattern recognition or non-pattern recognition categories. Non-pattern recognition approaches typically adopt a straightforward structure with minimal processing techniques [14]. Forearm EMG signal acquisition operates at a sampling frequency of 2 kHz, following the Nyquist sampling theorem's recommendation of a frequency at least twice the highest frequency within the signal.

The effective energy of the surface EMG signal is confined to the 0 to 500 Hz frequency range, with predominant energy concentrated between 50 and 150 Hz. This project involves a four-step data processing sequence: normalization utilizing maximum activation levels (peak amplitude) during maximum voluntary contractions, filtering via a band-pass filter, data segmentation using overlapping segmentation, and feature extraction employing the analysis of four-time domain features.

The normalization procedure, introduced by Eberhart, Inman, and Breslar in 1954, entails converting the signal to a standardized scale, providing a relative measure of muscle activation compared to a reference value. Typically, this involves dividing EMG signals during a task by a reference amplitude value (usually the maximum peak value) obtained from the same muscle. The choice of reference value is crucial for facilitating comparisons between individuals and/or muscles. Common methods for obtaining the normalization reference value include peak amplitude during maximum voluntary contractions (MVC), peak or mean activation levels during specific tasks, activation levels during submaximal isometric contractions, and peak-to-peak amplitude of the maximum M-wave. However, there is no universally declared best method for normalizing EMG raw data [14].

In this study, the maximum activation level (peak amplitude) during MVC is utilized to normalize EMG signals recorded from seven forearm muscles during manual muscle tests. These tests encompass isometric finger pinches and handgrip forces at various wrist positions and grip strengths (ranging from 20 to 100% grip strength). Each subject conducts three trials, pinching and grasping the hand dynamometer for 10 seconds, producing maximum forces with 5 seconds of rest in between.

The recorded maximum forces are utilized in the experimental procedure for data collection. MVC tests are conducted separately for each investigated muscle using multichannel EMG devices. The collected EMG signals undergo rectification and filtering before defining the maximum amplitude, indicating the maximum voluntary contraction of the specific muscles. The maximum value obtained during the test serves as the reference value for normalizing the EMG signals from the muscles of interest.

The EMG signal recorded during a task is subsequently divided by the reference value obtained from the same muscle of interest.

$$\text{normalisation} = \frac{\text{amplitude value}}{\text{reference value}} \times 100\% \quad (1)$$

Normalization is crucial for the precise interpretation of muscle excitation and proves highly beneficial in emphasizing statistically significant differences between the collected data classes, particularly when employed alongside standard hypothesis tests like the t-test and Anova test.

Following the normalization process, the data undergoes filtration using a second-order bandpass filter (20 Hz - 450 Hz) before segmentation. The segmentation employs an overlapping technique with a 256 ms window size and a 128 ms window increment within the MATLAB environment. The choice of overlapping segmentation offers advantages over disjoint segmentation, enhancing processing time and contributing to improved classification performance. The number of training samples is estimated as:

$$\text{No of training sample} = \frac{\text{Data length} - \text{window size}}{\text{window increment}} + 1 \quad (2)$$

Subsequently, the feature extraction process is initiated, playing a pivotal role in uncovering valuable information within the forearm EMG signals by converting raw data into a condensed representation in the form of a feature vector. This process is instrumental in eliminating undesired signal components and interferences. Drawing from studies conducted by Phinyomark et al. (2012), specific time domain features, namely mean absolute value (MAV), integrated EMG (IEMG), waveform length (WL), belonging to the energy and complexity information category, along with the frequency information method group, are selected for use in this research. This selection is made to avoid redundancy and ensure superior performance compared to alternative methods. Additionally, the root mean square (RMS) feature is incorporated into the analysis due to its adherence to normality and computational simplicity.

Root Mean Square (RMS) is widely embraced for feature extraction, modeled as an amplitude-modulated Gaussian random process. It is closely associated with the constant force and no fatiguing contraction of the EMG signal. The definition of RMS is as follows:

$$\text{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \quad (3)$$

In the equation, N denotes the total number of samples under consideration, and x represents the amplitude of the signal sample.

Mean Absolute Value (MAV) is computed as the average of the absolute values of the EMG signal over a specific time duration.

This method provides a straightforward means of detecting muscle contraction levels and stands as one of the most employed techniques in EMG signal analysis. The MAV feature can be expressed as:

$$\mathrm{MAV} = \left(\frac{1}{N}\right) \sum_{i=1}^{N} |x_i| \quad (4)$$

Integrated EMG (IEMG) entails the absolute summation of the amplitudes of the EMG signal, serving as a representation of the firing point in the sequence of EMG signals. This absolute summation is typically analyzed over a window length of EMG samples. The definition of IEMG is as follows:

$$\mathrm{IEMG} = \sum_{i=1}^{N} |x_i| \quad (5)$$

Wavelength (WL) is the cumulative length of the EMG waveform across a specific time segment and can be perceived as an extended version of the integrated EMG. It is defined as:

$$\mathrm{WL} = \sum_{i=1}^{N-1} |x_{i+1} - x_i| \quad (6)$$

2.3 Mind Wave sensing

A. Brain Anatomy and How the Brain Works

The brain, a multifaceted organ, governs thought, memory, emotion, touch, motor skills, vision, and various physiological processes [35]. Together with the spinal cord, it forms the central nervous system (CNS). Weighing around 3 pounds in an average adult, the brain is composed of approximately 60% fat, with the remaining 40% comprising water, protein, carbohydrates, and salts. Unlike a muscle, it houses blood vessels, nerves, including neurons and glial cells.

Gray matter and white matter constitute two distinct regions of the central nervous system. In the brain, gray matter, the darker outer portion, contrasts with white matter, the lighter inner section. This arrangement reverses in the spinal cord. Gray matter primarily consists of neuron somas, while white matter mainly comprises axons wrapped in myelin, serving different roles. Gray matter processes and interprets information, while white matter transmits it to other parts of the nervous system.

The brain communicates through chemical and electrical signals, interpreting various messages that regulate bodily functions. It relies on billions of neurons and can be divided into the cerebrum, brainstem, and cerebellum.

B. Brain Signals

Brain signals capture biometric information reflecting the user's mental state, whether passive or active. These signals model information processed by millions of neurons, resembling neural activity in both sensory and motor functions. Technologies analyze brain signals using traditional (EEG, MEG, MRI, fMRI) and non-traditional (Deep Learning algorithms, Decision Trees) methods. Feature extraction and classification processes play crucial roles in analyzing brain signals, offering insights into the user's mental activities [17].

Research by Phinyomark et al. (2012) highlights the significance of time domain features (MAV, IEMG, WL) and frequency information in processing forearm EMG signals [17]. These features, chosen for their efficacy and computational simplicity, aid in recognizing muscle contraction levels. Additionally, root mean square (RMS) is considered for analysis due to its normality.

C. Brain-Computer Interface (BCI)

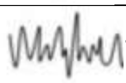
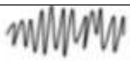
Brain-Computer Interface (BCI) utilizes brain signals to control external smart devices. These signals undergo processing using methods like Fast Fourier Transform (FFT), Wavelet Transform (WT), Time-Frequency Distribution (TFD), and others. Classification techniques, including Artificial Neural Networks (ANNs) and Support Vector Machine (SVM), enhance BCI capabilities. Brain signals, categorized as alpha, beta, gamma, theta, and delta waves, are recorded using electrodes through invasive or non-invasive procedures. Needle electrodes capture signals from interior brain regions, while surface electrodes follow a 10-20 placement system for cap-like positioning.

D. Invasive Procedures

Various invasive imaging procedures monitor brain electrical activity, including Electrocorticography (ECoG), Deep Neural Stimulation, and Invasive

Electroencephalography (EEG). ECoG, also known as intracranial EEG (iEEG), identifies epileptic regions and aids surgical evaluation. Deep Neural Stimulation employs electrodes to restore specific brain activities by delivering electric current, as shown in table 1.

TABLE 2 MIND WAVEFORM

Name	Waveform	Frequency (Hertz)	Activity
Delta wave		45294.00	Deep sleep
Theta wave		45390.00	Slow sleep/ drowsy
Beta wave		15-30	Exercise
Alpha wave		9_14	Resting
Gamma wave		>30	Thinking, problem-solving

E. MindWave

The MindWave Mobile Brain-Computer Interface (BCI) device, a revolutionary tool that translates your brainwaves into tangible actions, unlocking new realms of possibilities. The MindWave Mobile provides insights into the wearer's mental state using Narosky's exclusive Attention and Meditation eSense™ algorithms. This includes raw wave data and information about brainwave frequency bands. The NeuroSky MindWave Mobile seamlessly integrates with supported video games, research software, or various applications, delivering an unparalleled user experience. The MindWave Mobile Product Contents are as following: MindWave Mobile headset, MindWave Mobile Quick Start, and User Guide. While MindWave Mobile DVD contains Windows Frameworks, Connectors, and Utilities for MindWave Mobile, PC installation Executables, Bundle PC Apps, OS X Frameworks, Connectors, and Utilities for MindWave Mobile, Mac installation executables, Bundle Mac Apps. The configuration of the MindWave Mobile headset has been illustrated in Figure 9.

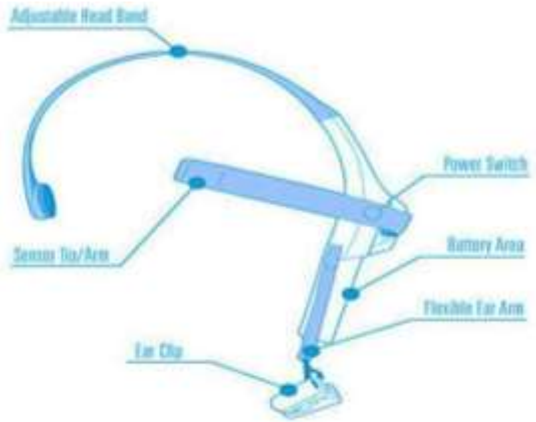


Figure "8" Configuration of the MindWave Mobile headset.

Wearing the MindWave Mobile is not your typical headset experience; it's a gateway to harnessing your brainwaves for exciting applications. Follow these steps for an optimal MindWave experience:

- Position the MindWave with the forehead Sensor Arm on your left side. Rotate the Sensor Arm about 90 degrees from its base for a proper fit. You can adjust it slightly more for comfort.
- Allow the rubber ear hoop to rest behind your left ear, then clip the earclip onto your earlobe.
- Ensure the two metal contacts inside both sides of the earclip make direct skin contact with your earlobe or ear. Move any hair or obstacles (like jewelry) out of the way.
- Fine-tune the earclip for proper skin contact.
- Squeeze the ear clip against your ear for a few seconds if necessary.
- Adjust the forehead Sensor Arm to ensure the Sensor Tip makes consistent contact with your forehead skin.
- Remember, the Sensor Tip must maintain steady skin contact for accurate brainwave measurement; it won't work through hair. The Sensor Tip should be comfortable, ensuring direct skin always contact. Makeup, dead skin, or debris may interfere, so scratch or wipe away obstructions for a clean signal.

This is how the properly worn MindWave should look. If you face signal issues during use, repeat the steps to make minor adjustments for optimal sensor and skin contact. Note that If signal quality problems persist, carefully review and recheck all instructions. Allow yourself to sit still for a few seconds, as talking may interfere with signal quality. If issues persist, ensure your head is not within a few feet of a strong electrical device, like a laptop adapter or electrical outlet.

Attention sense: The Attention meter gauges the user's mental focus or attention intensity, ranging from 0 to 100. Distractions, wandering thoughts, or anxiety may decrease the Attention meter level.

Meditation sense: The Meditation meter measures a user's mental calmness or relaxation on a scale of 0 to 100. While relaxation of body muscles may not immediately impact Meditation, it generally aids in achieving a relaxed mental state. Closing eyes often enhances Meditation, as it reduces the brain's active processes. Distractions, wandering thoughts, anxiety, agitation, and sensory stimuli may lower the Meditation meter levels.

Maintenance Tips can be summarized as follows:

- Periodically clean the MindWave's sensor and ear contacts with alcohol or a damp cloth to ensure optimal signal quality.
- Use a soft cloth to clean the MindWave casing.
- For travel and storage, gently push the sensor arm up without overextending it beyond the natural stopping point.
- Avoid exposing the MindWave to temperatures exceeding 140°F (60°C).
- Handle the MindWave carefully to prevent damage.
- Remove the battery when the MindWave is not in use for extended periods.
- Measuring Your Brain with MindWave: Hacking the Dongle
- To connect the MindWave dongle directly to Arduino, a modification is necessary:
- Remove the dongle cover and destroy the marked connection, as indicated.
- Confirm the broken connection with a multimeter.
- Solder wires to the dongle, ensuring proper color-coding.
- Red wire for the first pin marked with "+".
- Green wire to the dongle's TX pin.
- White wire to the dongle's RX pin.
- Black wire to the dongle's GND.
- Use a flux pen to facilitate the soldering process by improving the flow of old solder joints.

2. Results and discussion

A. Results

Initially, our quest led us to identify the optimal materials for the glove, focusing on lightweight and comfortable raw materials. After extensive exploration, we selected a material that perfectly balanced both attributes. The search for an ideal air unit culminated in the utilization of micro pumps, specifically a 6V micro pump, seamlessly integrated into the project. Employing two pumps facilitated the inflating and deflating of the glove, with a servo motor orchestrating the transition between them.[19]

The glove design underwent meticulous implementation in SolidWorks to visualize the final form, assess loads, and conduct stress analysis, ensuring mechanical robustness.

Our exploration extended to identifying the ideal board for project execution, leading to the selection of the Arduino Mega. To enhance user comfort, we evaluated different control methods and settled on two cutting-edge approaches:

EMG Sensor: This sensor detects muscle movements in the arm, streamlining glove control, expediting responsiveness, and enhancing the rehabilitation process.

Mind Wave: Modified to interpret nerve signals, the Mind Wave allows effortless glove movement during the rehabilitation process, requiring minimal effort from the patient.

The comprehensive project comprises a control box housing Arduino, pumps, and operational switches, EMG sensors transmitting muscle signals, Mind Wave interpreting nerve signals, and the gloves serving as the project's foundation, executing rehabilitation processes. Figure 13 illustrates the main components of the designed system. Figure 14 shows the experimental validation of the proposed system.

Figure “9” Experimental work[20]

Figure “10” Experimental work

Figure “11” Experimental work

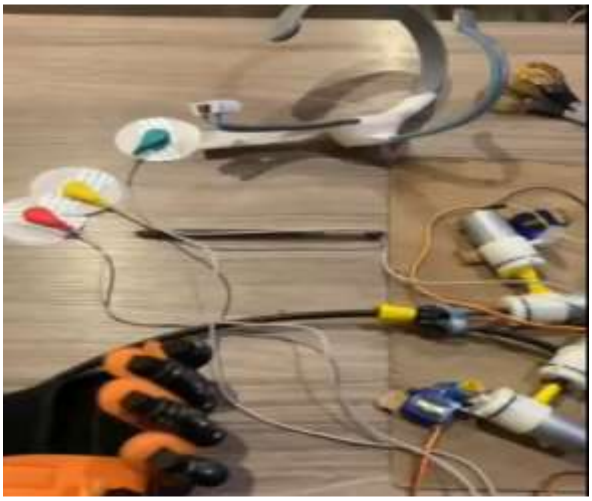


Figure “12” The main components of the designed system.

Figure “13” Experimental validation of the proposed system.

B. Limitations

There are the following limitations which have been conducted from the designed system:

- Weight: Striking a balance between lightweight design and adequate support can be challenging, potentially impacting usability.
- Size: Tailoring the glove to fit diverse body types may pose challenges in adaptability.
- Mobility: The glove's design might impose limitations on user movement and range of motion.
- Control and Feedback: Ensuring accurate interpretation of user movements for appropriate support and feedback can be complex.

- User Comfort: Maintaining comfort during extended wear is crucial; discomfort may hinder usability.
- Environmental Limitations: The glove's suitability in specific environments, such as high humidity or exposure to water, could be restricted.
- Regulatory Approval: Compliance with regulatory approvals may be necessary, adding complexity to development and marketing efforts.

C. EMG Results and Analysis

This section provides a detailed analysis of the raw and normalized EMG signals. Raw data collected at varying handgrip strengths for the flexor digitorum superficialis (FDS) muscle illustrates proportional amplitude changes. The trace also reveals envelope spikes indicating brain activity for muscle activation. However, challenges like AC line interference necessitate preprocessing for noise reduction, highlighting the importance of optimal data collection conditions.

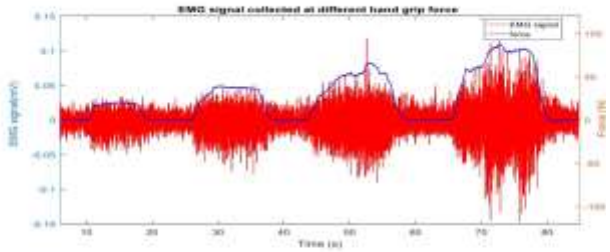


Figure "14" The raw EMG collected at different handgrip strength (20, 40, 60, and 80% of MVC) for FDS muscle at neutral wrist position

Conclusion

This paper addresses complications arising from brain trauma affecting the arm's palms. Modern methodologies, such as the mindwave sensor, read brain signals by gauging focus on a specific object. The project controllers are Mindwave Sensor, Pressure Sensor and EMG Sensor. Moreover, A detailed comparison of these microcontrollers is outlined in the preceding chapter. The focus now shifts to the EMG sensor, designed for measuring muscle activity by detecting electric potential, known as electromyography (EMG).

Traditionally employed in medical research, this sensor outputs 0-Vs Volts, depending on muscle activity. Electrodes read the voltage, offering a straightforward method to gauge and flex muscles. In addition, Muscle Sensing Kit provides all essentials for Arduino or controller-based muscle sensing activities. By employing the muscle sensor kit, users gain control through muscle activity. Distinctly, the mindwave sensor excels in signal reception, albeit with heightened software complexity.

In comparison, the EMG sensor measures muscle electrical activity, simplifying the hardware aspect. Furthermore, Force Sensing Resistors (FSRs) exhibits reduced electrical resistance upon increased physical force or pressure. As part of the piezoresistive category, FSRs function when force contacts the sensor, allowing controlled electricity flow. The electrical output varies predictably with applied pressure, enabling the detection of force changes. In essence, the AI-driven exoskeleton glove project explores a fusion of advanced sensors, providing a promising avenue for motor skill rehabilitation.

The distinct capabilities of each controller contribute to a comprehensive approach in addressing mobility challenges stemming from brain trauma. Utilizing artificial intelligence, the exoskeleton glove integrates actuators and touch sensors to aid patients in relearning manual tasks following hand, finger, or wrist mobility loss. Researchers highlight the proof-of-concept gloves' ability to guide wearers in piano-playing through a tactile understanding of correct and incorrect movements.

It should be noted that the presented pilot study should serve as an initial step in securing regulatory approval for a clinical trial involving stroke patients. The study is to provide valuable feedback on the device's comfort, and the collected quantifiable data consistently yielded replicable results for the performed repetitive motions. Replicability, denoting the device's ability to produce consistent, quantifiable results while operating predictably and reliably, assumes paramount significance in the design of a rehabilitation device.

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