

Neuroflex: A Real-Time, Wearable Neuro-Muscular Rehabilitation System Using Soft Robotics

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Abstract

Neuromuscular disabilities caused by strokes, paralysis, neurological damage, and muscle diseases could significantly decrease the functionality of the hand and upper limb and thus impede performing the activities of daily living. Even though the traditional rehabilitation method could help with restoring movement, the need for a therapist's control and the frequent visits to the clinic could limit access to therapy. In this paper, the development of Neuroflex, an assistive wearable robotic rehabilitation device driven by EMG signals is discussed. The system presented uses EMG signals collected through hand-attached electrodes and the collection and pre-processing unit based on ESP32. The time-domain parameters such as RMS, MAV, and variance are calculated from the processed EMG signals. A Support Vector Machine (SVM) classifier is used to classify muscle activity at four distinct levels, which include: at rest, low activity level, medium activity level, and high activity level. The output from the classifier is converted into the parameters of the rehabilitation process and sent to the Arduino Uno to control the MG995 servo motor that works with the 3D printed hand exoskeleton through the Pulse Width Modulation (PWM). A web-based interface is developed to monitor and visualize EMG parameters and system parameters. Experiments have confirmed the operational functionality of the proposed sensing, classification, and robotic assistance scheme.

Keywords: Electromyography (EMG), Support Vector Machine (SVM), Neuromuscular Rehabilitation, Robotic Exoskeleton, Hand Rehabilitation, ESP32, Arduino.

1. Introduction

Neuro-muscular impairments in conditions like stroke, spinal cord injuries, peripheral neuropathy, and neuromuscular disorders may lead to problems in the functioning of hands and upper extremities. Impairments in grasping, holding, writing, and activities of daily living may affect independence in performing everyday tasks. Treatment usually involves task-specific exercises through repetition, but the extent and regularity of rehabilitation may be restricted by relying on clinician-supervised treatment sessions.

The EMG system presents an effective physiological interface as it is capable of measuring the electrical signals produced by muscles and can give details about the intended movements even if the movements are hardly visible. Earlier experiments have shown that EMG control can be applied in manipulating the robotic hand and orthosis for rehabilitating and grasp assistance. Additionally, multimodal sensor techniques have been studied to enhance interaction between the user and the robotic hand orthosis while soft robotics techniques have showcased the benefits of compliant wearable devices for severely impaired people.

One of the important issues is the interpretation of EMG signals for transforming physiological activities to useful control actions. Classification of movement primitives and sEMG-based recognition systems have been studied in the field of upper-limb rehabilitation. In addition, deep convolutional learning as well as neural networks have shown their capability in modeling complex patterns in EMG signals. Nevertheless, for developing a real-time rehabilitation system, there should be a method that can operate on EMG features efficiently and computationally. SVM classifier seems to be a proper supervisory learning approach for this purpose and is thus selected in our project.

The proposed Neuroflex technology is based on the use of three-time domain EMG parameters: Root Mean Square (RMS), Mean Absolute Value (MAV) and signal variance for muscle activation description. The obtained features are categorized in four defined activation states: rest, low, moderate and high. The outcome of the classification is used for determination of rehabilitation parameters that will regulate the operation of the servo-based hand exoskeleton. Such an approach goes well with the methods of patient-cooperative rehabilitation when assistance is proportional to the user's input.

2. Related Works

A loss of functionality associated with upper limb movements due to stroke and other neuromuscular conditions can limit one's ability to perform activities such as grasping, carrying, writing, and even personal grooming. Rehabilitation for patients suffering from such disorders requires repetitive exercises specific to the task in order to enable motor recovery and muscle retraining. Traditional therapy-assisted rehabilitation, despite its effectiveness, may face some limitations due to the limited availability of therapists and the associated costs.

EMG has become an important interface for rehabilitation robotics because residual muscle activity can provide information about motor intention even when visible movement is limited. Gnocco et al. demonstrated EMG-based control of a supernumerary robotic hand for sub-acute stroke rehabilitation, establishing the feasibility of using residual EMG activity to drive robotic assistance [1]. Similarly, Meeker et al. investigated EMG pattern classification for controlling a hand orthosis and demonstrated its potential for functional grasp assistance following stroke [2]. Park et al. extended this concept by incorporating multimodal sensing, combining EMG with kinematic and force information to improve interaction with a robotic hand orthosis [3]. Harish et al. investigated wearable gyroscope-based motion tracking and hand gesture recognition, demonstrating the application of ANOVA for discriminating relevant motion features [4]. Soft robotic approaches have also gained attention; Ciullo et al. developed a soft robotic supernumerary hand for severely affected stroke patients, supporting the use of compliant wearable structures for rehabilitation [5].

Accurate decoding of EMG signals is necessary for adaptive rehabilitation. Parnandi et al. looked into the classification of movement primitives for stroke rehabilitation, showcasing the importance of breaking down movements into components that can be identified [6]. Bu et al. worked on sEMG-based upper-limb movement recognition using an advanced deep learning technique, whereas Zhong et al. developed a concept of fusion learning for recognizing various types of rehabilitation movements [7,8]. Kulwa et al. proved that the choice of signal window parameters can affect deep CNN in sEMG-based motion intent classification [9]. Contrary to all these techniques which were focused on deep learning algorithms, the current research uses a simple SVM classifier by selecting specific time domain EMG features. Moreover, the systematic review presented by Alam et al. reveals the growing usage of neural networks in

robot-assisted rehabilitation [10].

Gasperina et al. [11] summarized approaches toward adaptive assistance provided by exoskeletons depending on the participation level of the patients and gave the basis for the personalized rehabilitation. Xiloyannis et al. reviewed soft robotic suits and pointed out the advantages of wearable exoskeletons and issues related to sensing, control, and integration [12]. Ren et al. presented deep learning approach to the motion prediction in the control of upper-limb exoskeletons [13], and Wu and Chen presented the adaptive cooperative control for a soft rehabilitation exoskeleton [14]. Proportional myoelectric control principles discussed by Fougner et al. also give the basis for interpreting muscle activations into the command of the device [15]. All of the above gives evidence for integration of EMG sensing, machine learning, soft robotics, and adaptive control. Neuroflex incorporates all the above advances in a low-cost closed loop system.

3. Proposed Work

The design of the Neuroflex system involves a closed-loop model comprising muscle signals recording, signal pre-processing, feature extraction, machine learning classification, rehabilitation commands issuance, robotics control, and feedback. This model enables translation of the patient's remaining hand muscles activity to a suitable level of robotic help. Electrodes are positioned on the surface of the hand muscles that are responsible for finger and gripping motions. The recorded data are converted to digital format using the ESP32 microcontroller and pre-processed to filter out noise, baseline wander, motion artifacts, and electrode placement-related variations. Finally, the pre-processed signal is passed to the machine learning module.

Machine learning uses a SVM classifier with extracted EMG features such as RMS, MAV, and signal variance. The SVM classifier classifies muscle activity into four levels: rest, low, moderate, and high. The system determines the rehabilitation parameters of movement angle, speed, repetition count, and duration of exercise based on the output from the SVM classification. The SVM classification output is mapped to the pre-defined rehabilitation parameters, and this enables the robotic assistance to vary depending on the muscle-activation level.

Table 1. Mapping of SVM-classified activation levels to rehabilitation control parameters

Activation	Servo Angle(°)	PWM(μ s)	Speed(°/s)	Repetitions	Duration(min)
Rest	90	1500	0	0	0
Low	105	1583	15	5	5
Moderate	120	1667	30	10	10
High	135	1750	45	15	15

SVM classification is training with the extracted EMG feature vectors expressed as $X=[\text{RMS}, \text{MAV}, \text{Variance}]$ where muscle activation level is taken as the class label. When the system is working in real time, the SVM classification is done based on the input feature vector taken from the EMG signal and the activation class is predicted. Then, the output from SVM classification is translated to the control commands according to the mapping relationship as indicated in Table 1 where the higher muscle activation level corresponds to a higher angle, PWM commands, movement speed, repetitions, and exercise duration.

Selected values for rehabilitation are then provided to the Arduino Uno that produces PWM signals for the MG995 servo motor. Servo motor controls the motion of the 3D printed exoskeleton providing controlled movement of the hand or arm. Restrictions on maximum motion angle and speed are considered when designing control logic in order to increase safety. In real-time process of the system, the EMG signal is constantly measured during the movement carried out by the exoskeleton. Thus, changes in muscle activation can be used for control decisions in the future, and the system will be able to change its assistance depending on detected muscle activation. Such patient-controlled approach can be regarded as a patient-cooperative one [10,13].

4. System Architecture

The implementation comprises three inter-related functional layers (refer to Figure 1). Sensing layer is composed of EMG electrodes, EMG sensor, and ESP32 which are responsible for acquisition and conditioning of physiological signals. Processing layer is comprised of computer-based Python module, which does EMG features extraction, classification using SVM algorithm, and calculation of rehabilitation parameters. Actuation layer is comprised of Arduino

Uno, MG995 servo motor, and 3D-printed exoskeleton that transforms generated commands to mechanical movements.

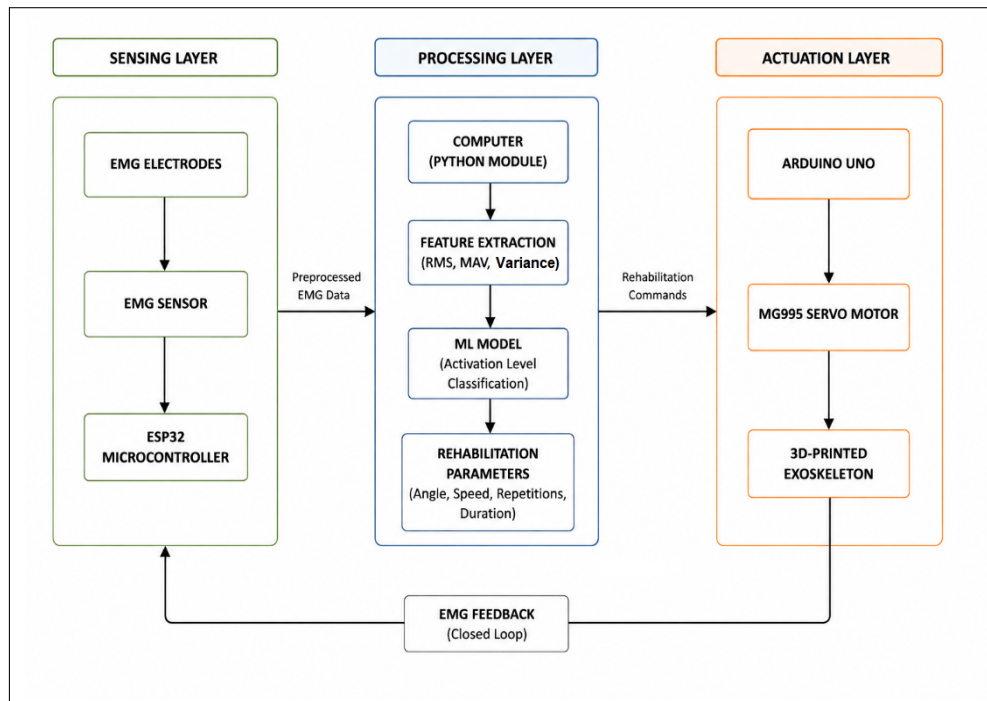


Figure 1. System architecture of wearable neuro-muscular rehabilitation system

The web-based user interface that uses HTML and JavaScript code to visualize the levels of EMG, predicted rehabilitation levels, and the performance of servo. The whole process sequence is illustrated in Figure 2.

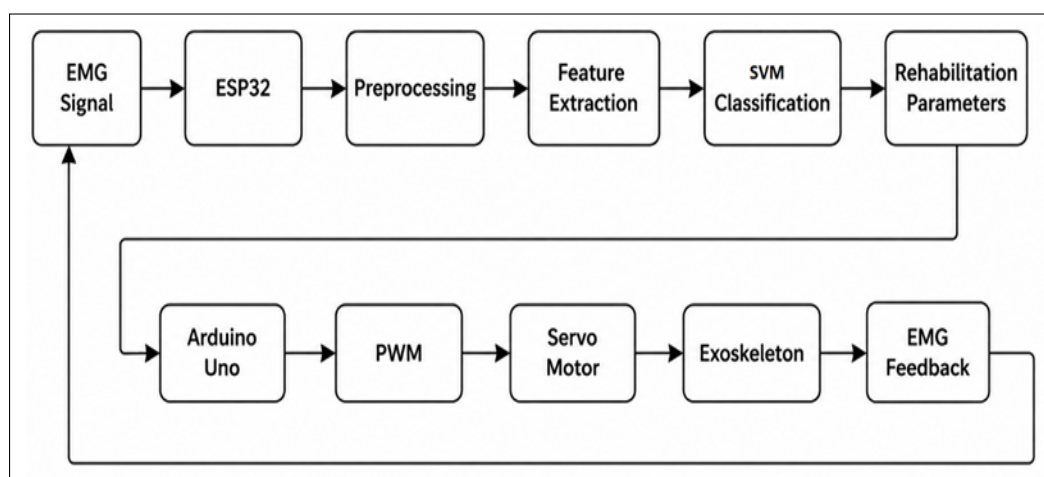


Figure 2. Operational sequence of the Neuroflex system

5. Hardware Implementation

The hardware architecture used for the development of the Neuroflex prototype comprised of an EMG sensor module, processing unit, control unit, actuator, mechanical exoskeleton, power supply, and computing platform. These modules were selected for performing the process of acquiring hand muscle activity and converting it into therapeutic movement. The hardware architecture along with their respective functions is tabulated below in Table 2.

Table 2. Hardware configuration of the proposed system

Hardware Component	Function
EMG Sensor and Electrodes	Acquire surface electrical activity from the intrinsic hand muscles during voluntary muscle activation.
ESP32 Microcontroller	Performs signal acquisition, analog-to-digital conversion, pre-processing, normalization, and communication with the processing unit.
Arduino Uno	Receives rehabilitation commands and generates PWM signals for actuator control.
MG995 Servo Motor	Provides controlled angular actuation for the rehabilitation mechanism.
3D-Printed Exoskeleton	Provides the mechanical interface between the actuator and the user's hand/arm.
9 V Battery and Connector	Provides portable power for the prototype.
Jumper Wires and Fasteners	Provide electrical interconnections and mechanical assembly support.
Laptop/Computer	Runs the Python-based machine-learning module and real-time monitoring interface.

The EMG sensors are placed over the intrinsic hand muscles, hence enabling the system to acquire the EMG data from muscle movements during attempted or voluntary movements. The ESP32 microcontroller acts as the embedded unit, where preprocessing of the acquired EMG data takes place. Once preprocessed, the EMG data is relayed to the computer where machine learning is applied. The output from machine learning is then given to the Arduino Uno microcontroller, which activates the MG995 motor through the PWM signals. The actuator

is linked to the 3D printed exoskeleton (refer to Figure 3).



Figure 3. Hand-mounted robotic exoskeleton used for rehabilitation

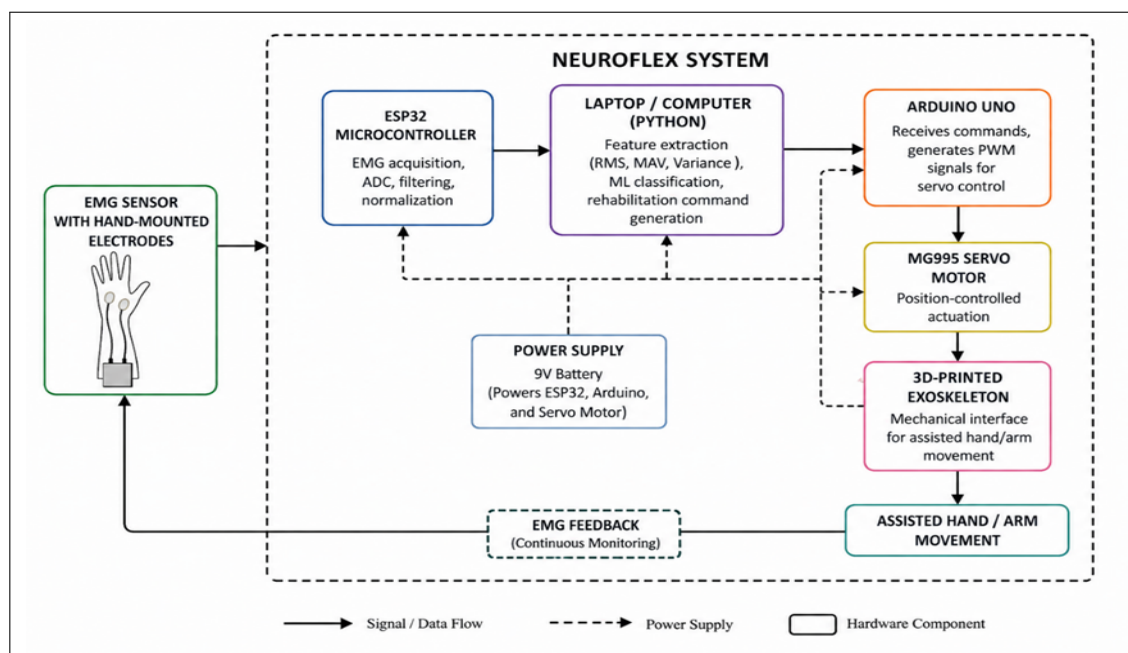


Figure 4. Hardware implementation design of the Neuroflex system.

Figure 4 indicates that the mechanical assembly is constructed with the aim of facilitating mounting, alignment, and stability. This is critical because any unnecessary mechanical movement may not only cause discomfort to the person using the device but may also impair the accuracy of the assistive movement generated.

6. Software Implementation

The system architecture was designed for seamless processing and control flow starting from the acquisition of EMG signals to the actuation of the robot. The different components used in this include the embedded firmware for ESP32, machine learning backend through Python, Arduino firmware, and web monitoring interface. The functions of each component are shown in Table 3.

Table 3. Software and platform configuration

Software / Platform	Configuration / Purpose
Arduino IDE	Development environment for ESP32 and Arduino firmware.
ESP32 firmware	EMG acquisition, filtering, normalization, and serial transmission.
Python	EMG feature extraction, SVM classification, and rehabilitation-command generation.
SVM Classifier	Classification of EMG-derived muscle activation levels into rest, low, moderate, and high activation classes.
EMG feature extraction	RMS, MAV, and signal variance.
Arduino firmware	Command decoding and PWM generation.
HTML	Structure of the real-time monitoring interface.
JavaScript	Real-time dashboard interaction and visualization.
Serial communication	Data exchange between ESP32, Python backend, and Arduino.

The software architecture uses the sequential processing pipeline structure. The ESP32 pre-processes the received EMG signal, while the Python back-end selects the needed features and runs the trained SVM classifier for the determination of the muscle activation stage. The results of classification are used to convert them into the rehabilitation parameters, which are then transferred to the Arduino Uno board for motor signals generation.

7. Results and Discussion

The Neuroflex dashboard allowed one to monitor the acquired EMG signal and activity parameters in real time. For the current session of monitoring, there were 1000 data points with an average EMG of 70.7 μV and an instant value of 0.0 μV . The fatigue index, according to the

dashboard, is 0.0%, no contractions detected, an average contraction duration of 0.00 s, and an activity ratio of 0.0%. The SNR value was 1.01, and according to the dash, the signal quality was poor. The SNR stands for the quality of the acquired EMG input and cannot be considered an indicator of SVM performance. A lower SNR means that the noise contributes to the EMG input more than the signal itself and thus impacts the stability of the RMS, MAV, and variance parameters. As those parameters are used by the SVM classifier, decreased signal quality can affect the accuracy of classification and, ultimately, the stability of the activation class, which is the input into the command for robot rehabilitation.

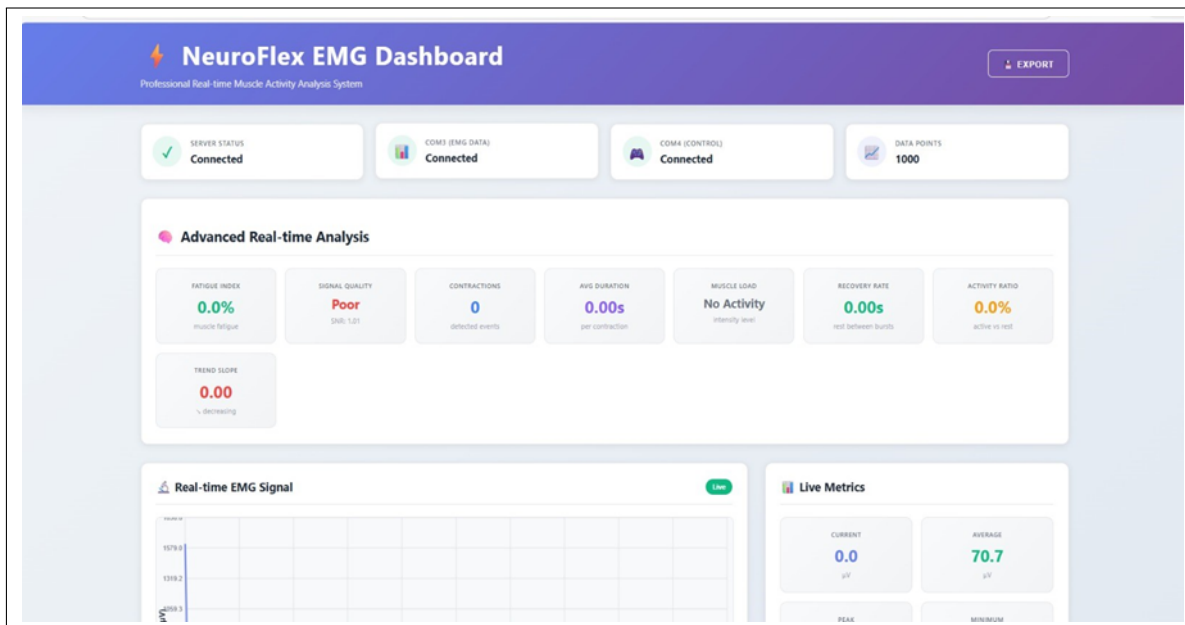


Figure 5. NeuroFlex EMG dashboard

During testing, the EMG amplitude variations led to differences in the rehabilitation behaviour. The smaller the amplitude, the less was the assistance provided; similarly, the larger the amplitude, the more movement was commanded. Such behaviour shows that the prototype was able to change the rehabilitation behaviour based on the muscular efforts made by the user. This behaviour is especially important with respect to our goal of developing a patient-responsive system.

The experimental observations have also confirmed that the communication between the processing and control blocks was stable. Data transmission did not experience any packet losses during operation. The actuator has been set to the desired position reliably, while mechanical parts demonstrated practically imperceptible vibrations and backlash in the course

of experiments. These observations suggest satisfactory coordination of electronic control and mechanical parts of the prototype.

Another important observation was the closed loop reaction. The change in EMG activity in response to the assisted movement was captured through the system reaction, proving that the output was not independent of the physiological response of the individual. This proves the viability of using the muscle activity observed as the basis for modification of the rehabilitation assistance. However, the current assessment only proves functional ability.

Overall, the results clearly indicate that the prototype has been successful in meeting its objective of detection of variation in muscle movement with the provision of an appropriate response from the robot. However, the present outcome should be viewed cautiously since the evaluation was qualitative in nature with a small sample size of healthy subjects. The present study did not give any statistical data regarding accuracy of classification, tracking error, and clinical recovery of the patient. Thus, more data is needed for assessing the efficacy of the system.

8. Conclusion

This work proposed Neuroflex, which is an EMG-based wearable prototype system designed for rehabilitation purposes using SVM classification for relating EMG signals to robotic assistance. RMS, MAV, and signal variance features were computed from recorded EMG signals and classified into four predefined activation levels. Based on the classification output, rehabilitation parameters were generated for driving a 3D printed servo-driven hand exoskeleton robot. The experimental observations confirmed real-time monitoring of EMG signals, consistent module-to-module communication, actuation control, and adaptation to any change in muscle activation level. This work has proven the concept of using EMG monitoring, decision-making through SVM classification, and robotic assistance in a closed-loop rehabilitation system. However, the current study had its limitations in terms of scalability and did not validate the effectiveness of the technique either clinically or quantitatively in terms of classifier performance. Therefore, further research needs to be carried out using more datasets, validating SVM classifier through motion tracking, among others.

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