Efficient Early Prediction of Hand Movements Using Two-Channel Electromyography Signal Analysis

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Abstract

The electrical activity produced by muscles is recorded by the electromyography signal, a dynamic biosignal. This dynamic nature represents the complex muscular behavior patterns. Electromyography - based recognition systems have far-reaching effects, revolutionizing human-computer interactions, enabling sign language detection, and giving amputees greater control over their devices.

This study aims to predict specific hand movements by analyzing electromyography signals from a minimal number of channels. The computational cost efficiency of this approach makes it suitable for real-time applications. Electromyography signals were collected from the forearm muscles of 15 healthy subjects (5 women and 10 men) aged between 19 and 24. Preprocessing tasks were applied to the raw signals, including high-pass filtering, Butterworth filtering, notch filtering, and signal rectification.

The dataset consists of recordings from four channels, of which two channels were selected for predicting hand movements. Two 500 ms time windows from both channels were used as inputs for a weighted K-Nearest Neighbors algorithm. The task involved predicting and classifying the intentions of three hand movements: pinching, finger abduction, and grasping.

The procedure's overall results demonstrate 83.1% detection accuracy for the weighted K-Nearest Neighbors indicating high precision and a relatively short response time for predicting these hand movements in healthy subjects.

Keywords: Electromechanical delay, Electromyography signal, Weighted K-Nearest Neighbors, Hand movements

1. Introduction

The dynamic interaction between people and computer systems, such as robots, has attracted substantial interest and has been the focus of numerous modern research studies over the past decade [1]. According to the World Health Organization (WHO), more than 15 million individuals suffer from stroke annually. Presently, stroke is the most common illness, characterized by a disruption in blood flow within a specific area of the brain [1]. Typically, stroke patients experience a loss of control and mobility in their upper limb muscles [3]. While there has been notable research in the field of motion recognition, there remains ample room for progress, especially in the area of motion prediction. By concentrating on the advancement of motion prediction technologies, we can enhance the capabilities of Robotic Orthoses and open up new avenues for assisting individuals with disabilities and ultimately improving their quality of life. Moreover, these predictions can be employed to alleviate the issue of time delay in the systems containing human operator in the loop [4] [5]. The majority of the time, predicting muscle activations using optimization techniques requires computationally intensive methods [6]-[7]. Short-term rehabilitation programs have shown promise in addressing muscle activity issues. These programs rely on surface electromyography (sEMG) signals, which are generated during various muscle contractions [8]-[9]. Recently, sEMG signals have been employed to identify intricate patterns of skeletal movements. For instance, they have been utilized in rehabilitating hand movements for stroke patients and in controlling robotic hand motion [10]. Although there have been many research studies to establish passive systems [11]-[12] as a basis for controlled walking [13]-[14] and rehabilitating systems [15], analyzing muscle signals (EMG) from various regions creates opportunities for enhancing upper and lower body prostheses and rehabilitation systems. Such rehabilitation systems include passivity-based prosthetics [16], and minimally actuated gait rehabilitating systems [17]-[18]. Industry adoption of collaborative robots is rising as they offer flexibility and higher output for difficult tasks. However, because of their poor sensory input and inability to understand humans and adapt to their behavior, robots are still not interactive enough. One technique to enhance these robots would be to predict human movement intentions [19]. Also, the use of exoskeletons and prostheses has been increasing in the last decade, and among them, those incorporating EMG signals are of particular interest to scientists in the field. Hand functions such as gripping and grasping are basic needs of an amputee which can improve their social performance and thus their self-esteem [20].

EMG can be used to calculate and determine the force and the trajectory of the movements. It can be used to detect EMG signals continuously to help the exoskeleton move more accurately and measure muscle effort. By using this method, subjects can control the exoskeleton much easier and adapt faster and better to it [21]. For instance, there are many different methods to control a bionic hand, and among them, using sEMG can bring high accuracy and more comfort for users. In this method, users can do different tasks with good performance [22]-[23]. Furthermore, extracting features from EMG signals needs a significant amount of time; as a result, new techniques should be applied to get the same outcome in a shorter time [24]-[26]. Moreover, for controlling the wrist exoskeleton, surface EMG can be used to classify movement patterns. In some studies, four EMG channels were used to determine the torque generated by two different subjects [27]. EMG-based prediction of hand gestures can also be used as a complementary method for predicting future human motions within systems encompassing network delays [28][29]. Many previous studies have focused on recognizing the movements of the hand and finger by getting and analyzing EMG signals [31]-[33]. For example, in [34] they captured motions using cheap and reliable accelerometers placed around the forearm. The potential for a reliable hand gesture detection system based on accelerometer signals is assessed in this work since accelerometers can be simply integrated into mobile devices. For this, two different types of recurrent neural network (RNN) cells are proposed in a neural network architecture. Studies on three datasets show that this relatively modest network performs significantly better than cutting-edge methods for hand gesture detection that rely on multi-modal data. A strong hand gesture classification system was created by combining accelerometer data with an RNN; as a result, network performance was consistent across participants and excels for amputees. Additionally, the suggested network classifies the hand motions using only 5 ms-long small windows. As a result, this method enables a possibly delay-free and rapid hand motion detection. However, few works have worked on movement prediction, delay time, and other affecting conditions such as the effect of the aging process on the electromechanical delay [35]. Different approaches have been proposed to discriminate the delay between the onset time of electrical activity and muscle movement. For different muscles, different electromechanical delay times are observed. There are some research works studying the dependency of this delay on different initial conditions, the difference in delays for different muscles, and the dependency of the time delay on the contraction type (whether the movement is eccentric, concentric, or isometric) or its independency from movement complexity and movement duration [36]-[38]. Electromechanical delay can be separated into two parts; the first and shorter part is the transport time which is about 10ms, and the second part is the time that muscle generates a force that can be detected [39]. Muscle reaction time can be increased by fatigue or sprint training, and therefore electromechanical delay can be increased after these training trials compared to the situation before the training [40]. In some works, they studied the effect of a six-week training period on the electromechanical delay and reaction time. Reaction time was shown to be reduced by training individual muscles, while the electromechanical delay of some of these muscles increased after this training program [41]. Some other studies showed that reaction time depended on the type of movement (voluntary, reflex, and electrical stimulation) [42]. In [43], they look into the possibility of anticipating hand motions using sEMG signals to solve the time delay issue with traditional classification techniques. Early prediction, compared to classification, seeks to foresee a future hand movement based on available data. A hand prosthesis control system may be able to make up for the time delay thanks to its early prediction capability, which will enhance usability. It has been demonstrated that using historical data from before the current time window is crucial for enhancing performance on tasks requiring categorization as well as prediction. Researchers presented a method for anticipating hand movements using recurrent neural networks (RNNs) and a novel weight-based loss function [44], to make predictions of hand motions easier. This new loss function, dependent on the particular time step, assigns different weights to the outputs of an RNN at various time points to calculate the final loss. To overcome the low sample availability during instances of hand movement changes, they also included a sample weighting scheme as part of this loss function. They used the Ninapro database to show how their suggested strategy improves early movement prediction performance and produces cutting-edge classification results for hand movements. Even some research [19] offers a system that predicts the intended direction of a human arm movement simply from eye gaze, using a recurrent neural network. The system leverages the concept of uncertainty to decide whether or not to accept a prediction. The deep learning approach that is being presented produces predictions on continuously arriving data achieves an accuracy of 70.7% for highly definite predictions and accurately categorizes 67.89% of the motions at least once. Before the hand reaches the target and more than 24% earlier than expected in 75% of the situations, the movements are accurately predicted 99% of the time the first time. This implies that a robot might get alerts on the direction an operator is expected to walk, and it might then modify its behavior accordingly. Moreover, in [45] they focused solely on predicting gripping force during a pinch-type grasp from surface electromyography (sEMG) data.

This study represents a significant advancement in the field of Electromyography (EMG) applications by addressing essential aspects of response times, which are crucial for practical applications. Our main goal is to accelerate movement prediction, ultimately reducing the electromechanical delay period, the amount of time it takes for an intended action to be executed. By simplifying EMG-based processes, our research aims to pave the way for faster and more efficient applications, particularly in fields such as rehabilitation and assistive technology. We employed a systematic approach, ensuring the precise placement of single surface electrodes on individuals' forearms to maintain non-invasiveness and accuracy in data collecting. We just used two channels to simplify the prediction process, which increases the accessibility and usability of our methodology. This simplification improves the usefulness and simplicity of implementation. To ensure the reliability and robustness of our findings, we evaluated our predictions using four distinct methods. Our results are assured to be accurate and resilient by this multifaceted evaluation approach, which lays a strong basis for future applications. This work represents a significant step forward in improving the usability and efficacy of EMG-based in predicting hand movements. By focusing on only two channels, our methodology simplifies the prediction process, making it more accessible and easier to implement while maintaining high accuracy. The advancements presented in our study have the potential to improve people's lives. Our goal is to improve the quality of life for users by lowering the electromechanical delay period and optimizing the EMG process to aid in the development of more responsive and efficient solutions in assistive technologies and rehabilitation.

2. Materials and Methods

2.1. Method

The tests were taken from fifteen healthy volunteers (five females and ten men, ages 19-24) from the local population of Tehran Iran. The medical history of all subjects was clear of any neural and muscular disorders. The procedure was explained to the subjects, and each participant verbally expressed his/her consent before the test.

2.2. Task Definition

Subjects were asked to sit comfortably in front of a monitor in a dark room covered by acoustic foams. Subjects were asked to put their right forearm on the table with a 90-degree elbow angle and their right hand's palm perpendicular to the table. Five hand gestures were shown to subjects (Fig. 1), and three of them were selected for classification:

1. Pinching: grasp with thumb and index finger

2. Grasping: clenching the fingers and thumb into the palm

3. Finger abduction: to draw away the thumb and fingers from each other.

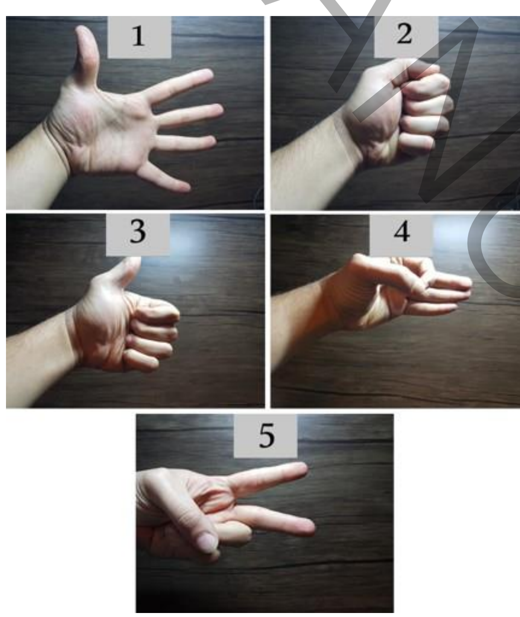

Fig. 1: Five movements conducted in the test: 1) finger abduction, 2) grasping, 3) grasping without thumb involvement; that is, four fingers in flexion and thumb in extension 4) pinching, 5) scissor; that is, abduction of the index and middle finger toward each other while other fingers are in flexion.

Each subject performed a four-sectioned task within a 15-minute rest in between and each section contained 40 trials (every section included eight trials resulting in 32 trials for each movement). For every 10 seconds, the monitor showed one of the hand gestures with a counter on it, counting down from 3 to 1 was done first, and we asked the subject to perform the motion after finishing this count. The time of the onset was extracted by a photodiode attached to the corner of the monitor and triggered by the change of pictures.

2.3. EMG Recordings

EMG signals were recorded by a 16-channel system (eWave, ScienceBeam Inc). The signals were recorded by 1024Hz sample frequency. Eight self-adhesive bipolar electrodes were attached in a circular shape with equal distances around the forearm. Electrodes were connected to the proximal part of the forearm, 2.5cm below the inside of the elbow while the distal set of electrodes were attached 5cm below them (see Figs. 2, 3, and 4). The ground electrode was attached to the opposite hand, on the wrist, on the head of the ulna. During the casual approach, electrodes are placed on the target muscle, but in the mentioned configuration, electrodes will record a variety of muscles.

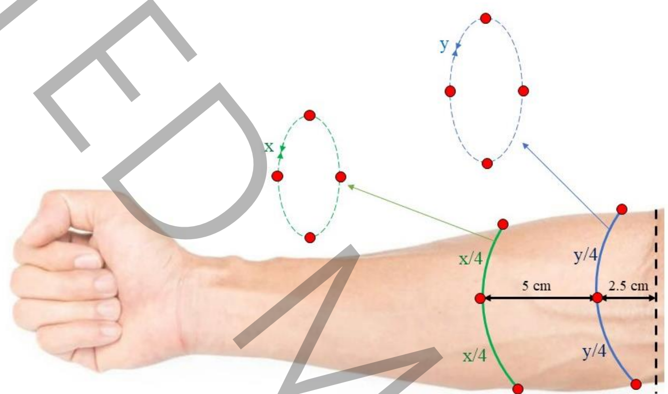

Fig. 2: Electrodes placement on the right forearm in a circular shape

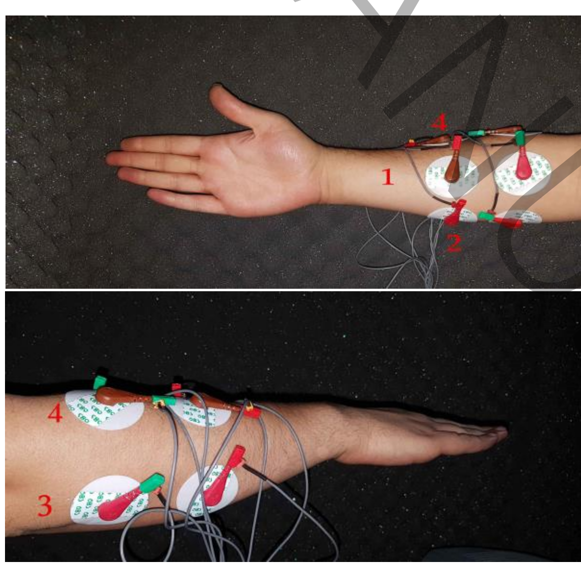

Fig. 3: Electrodes are attached to the forearm, 2.5cm under the elbow in a circular pattern. Electrode #1 is placed in the middle of the anterior of the forearm while the position of other electrodes is toward the medial view.

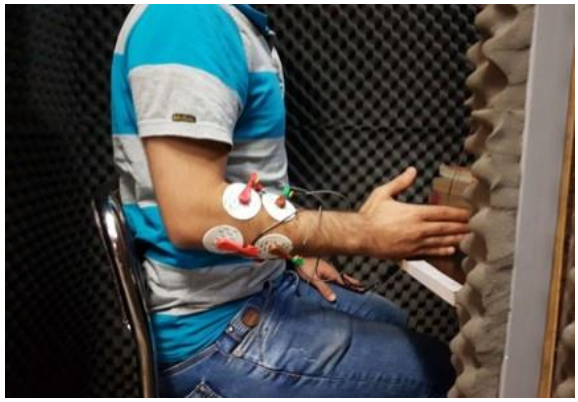

Fig. 4: The subject is sitting relaxed on the chair while his forearm is parallel to his thigh and the ankle is in the right angle. The electrodes are arranged in a circular pattern.

2.4. Electrodes Arrangement

Each electrode obtains a signal from more than one muscle which will have its benefits and drawbacks. Firstly, by this method, more muscles can be covered by fewer electrodes which will reduce the time costs. secondly, in each movement, more than one muscle will activate which needs to cover all the related muscles. For example, for pinching, in these arrangements for each movement, all the muscles engaged in the activity will be covered.

2.5. Signal Preparation and Feature Extraction

Trigger signals generated by the photodiode occurred 500ms before the onset times. This timing precision allowed us to meticulously isolate and extract data for individual trials from the extensive recorded signal. MATLAB software was used to process the EMG signals. Afterward in the first step, the raw signal was filtered by high pass Butterworth (5th order filter, with a cut-off frequency of 10Hz), then rectified and finally taken root mean square (RMS) with 200ms time window. To extract features more effectively, smoothing of the signals is recommended. Smoothing can be done with either a low pass filter or RMS; here, we applied RMS. After this, the signal preparation is almost accomplished and it is prepared for feature extraction. After signal preparation, the relevant features must be extracted to distinguish the three desired movements mentioned above. Two of four channels were used to reduce the computation cost and time. In this work, channels #2 and #4 were selected to distinguish the three above-mentioned movements, and four features were extracted from the signals recorded by these two channels. Signals should be normalized so that different subjects can be compared to each other according to their corresponding (normalized) signals. Each signal (taken from the individual subject) was normalized concerning the maximum value of that signal; as a result, we obtained normalized signals with values from 0 to 1.

Our main goal was to develop a predictive model that could recognize different kinds of movements. To achieve this, we paid close attention to the signals that precede the onset of each movement. Here, "onset" refers to the initial onset of a physical muscle movement. We delved into analyzing these signals to gain insights into the patterns preceding movement initiation. Hence, we carefully selected a segment of the signal spanning approximately 500 milliseconds, starting from the moment the photodiode triggered to when the onset of the movement occurred. This timeframe was selected to capture the critical period leading up to the initiation of the movement, providing us with valuable insights into the pre-movement dynamics. This section, which represents the signal from the moment the subject saw the motion on the monitor until the moment the subject was requested to do the motion, was referred to as the "pre-onset signal". For channels #2 and #4, the mean values of this part of signals (pre-onset signals) could potentially be two features. However, using solely these two features to distinguish different movements might lead to inaccurate results, thus, we should look for additional features to gain better results. We noticed that in some movements, the mean values of pre-onset signals were close to each other, but the maximum value corresponding to a certain movement was higher than that of others (Fig. 5), it is clear that when doing finger abduction and pinching motions, the maximum value for channel #4 exceeds that of channel #2 by approximately 0.4 and 0.2, respectively. Conversely, during grasping gestures, channel #2 exhibits a maximum value of approximately 0.3 higher than that of channel #4. Therefore, the maximum values of pre-onset signals were considered as additional features. In conclusion, there were four unique features in our final feature set. The mean values of the pre-onset signals for channels #2 and #4 were used to generate two of these features, while the maximum values from the same channels were used to generate the other two. Moreover, we have shown the steps of processing in Fig.6.

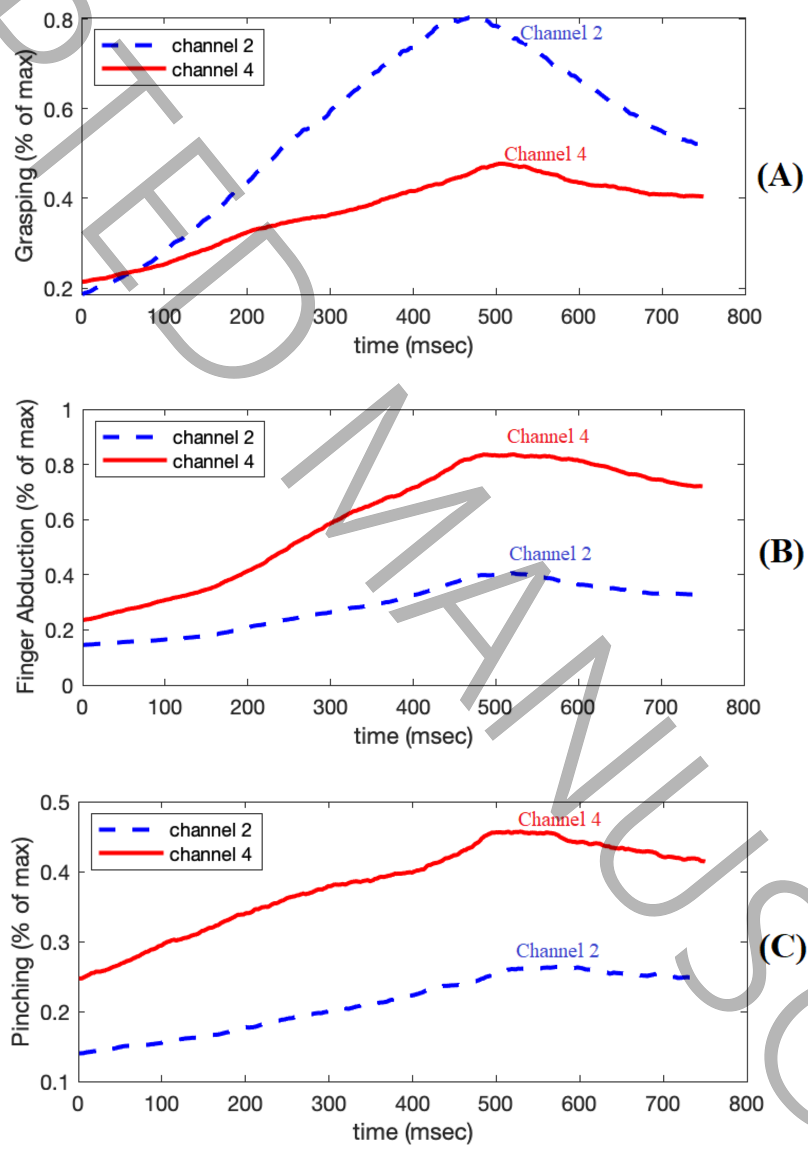

Fig. 5: The average signal of all subjects in two channels #2 and #4 for three movements: A) grasping B) abduction of fingers C) pinching; The blue curve represents channel #2, and the red curve is channel #4

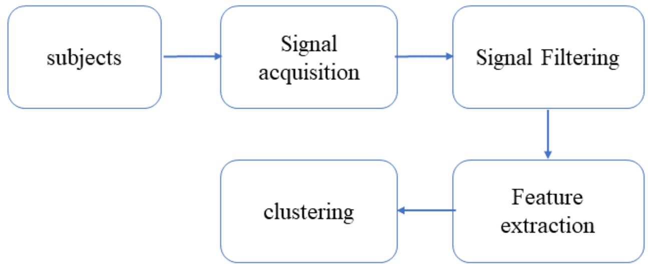

Fig. 6: The Block Diagram of our Finger Movement Prediction Study

3. Results and Discussion

In terms of predicting motion, the second version of the database from the Ninapro project was used in various studies, including [43] for testing the early prediction approach [46], there are sEMG signals for 50 different hand movements (including rest) in the database. Twelve electrodes were positioned around the subjects' forearms for the purpose of signal capture. Train data alone was used to calculate the requisite statistics. The signals were then divided into overlapping windows with a 95% overlap and they were able to anticipate events up to 300 ms in the future with an accuracy of less than 83% of the early predictions were accurate on average across all subjects.

In this study, three different algorithms were used for clustering purposes. The fuzzy classification approach was the first prediction method; instead of using strict binary assignments, this method classifies objects according to their degrees of membership to distinct classes. It makes it possible to describe uncertainty in a more flexible way, where objects can belong to multiple classes to varying degrees, the second approach was the optimized fuzzy classification where the fuzzy conditions had been optimized by Genetic Algorithm (GA); GA is an optimization technique based on natural selection, which iteratively improves the parameters of the fuzzy system to increase its accuracy in classifying data points, and finally, the third approach was the Weighted K Nearest Neighbors (W-KNN) regression method. In W-KNN, the influence of each neighbor is weighted according to how far away it is from the data point being classified, providing a flexible and effective approach for clustering tasks.

To construct a fuzzy classifier, we defined 4 fuzzy rules listed in Table 1. Each rule would assign a score or a penalty to the pre-onset signal for each movement. Finally, the overall score of each signal determined the movement. The results for the fuzzy classifier have been tabulated in Table 2 for 15 subjects. As can be seen, the classification accuracy rate is an average of 71.18% which is not so satisfactory.

Table 1: The rules of scoring four features for a simple classifier

Rules	Correct	Incorrect
If the mean of channel 2 is less than 0.5	+1	-1
If the mean of channel 4 is less than 1	+1	-1
If the maximum of channel 2 is less than 0.8	+1	-1
If the maximum of channel 4 is less than 0.8	+1	-1

This result led us to optimize the fuzzy rules; we utilized the Genetic algorithm (GA) for the optimization method using the GA toolbox of Matlab software. The cost function was a function of the average accuracy percentage; that is:

$$\text{Cost Function} = 1 - (\text{Correct Answers}\%) \tag{1}$$

Table 2: Accuracy of predicting each movement for each subject using a simple fuzzy classifier

Subject	Total%	Abduction%	Grasping%	Pinching%
#1	87.50	84.38	100	78.13
#2	63.54	9.38	84.38	96.88
#3	77.08	46.88	90.63	93.75
#4	61.46	100	84.38	0
#5	57.29	40.63	78.13	53.13
#6	46.88	37.50	31.25	71.88
#7	69.79	81.25	93.75	34.38
#8	64.58	43.75	62.50	87.50
#9	50.00	31.25	56.25	62.50
#10	81.25	100	87.50	56.25
#11	61.46	31.25	62.50	90.63
#12	82.29	81.25	90.63	75
#13	94.79	96.88	90.63	96.88
#14	92.71	100	81.25	96.88
#15	77.08	75.00	84.38	71.88

Table 3 presents the refined set of rules that form the basis of our optimized fuzzy classifier. These rules were carefully crafted based on the insights gained from the Genetic Algorithm (GA) optimization process. With the help of each rule's conditions for scoring four attributes, data points can be precisely classified. Through meticulous adjustment of parameters, the optimized rules ensure enhanced accuracy and reliability in categorizing movements.

The outcomes of using our improved fuzzy classifier to forecast different moves for every subject are shown in Table 4. The average classification accuracy rate is an incredible 74.03%, which is a notable improvement above the results of the basic fuzzy classifier. The aforementioned table presents the percentage accuracy of predicting various movements for every subject, showcasing the effectiveness of our optimized approach in achieving more precise and reliable data categorization. These findings highlight the value of optimized fuzzy rules to better align with the complexities of the dataset, ultimately leading to superior classification outcomes.

Finally, the last method utilized to classify the inputs was the W-KNN algorithm. According to this algorithm, classification is based on the calculation of the distance of an unknown signal from all classes; then its proximity to the nearest class would determine its corresponding class.

Therefore, the distance of each movement is compared to the predetermined movements based on the selected features. By selecting $K = 10$ as the input to this method, and also using Matlab software which has W-KNN as an embedded toolbox, the classification was accomplished; the results for this part are listed in Table 5 in which it can be seen that the average accuracy percentage is 83.1% which is considerably higher than previous methods.

Each channel targets multiple muscles with certain movements, and because of that, in each channel, specific movements have more power than others. To explain this, for example, channel #2 covers the Flexor Digitorium Superficialis and Flexor Digitorium Profundus muscles which are responsible for grasp. Although Opponents Digiti Minimi muscle and Lumbricals of the hand are also both hand flexors, they do not reach to channel area. Since these muscles are farther away from channels one, three, and four relatives to channel #2, their movement signals could be traced by channel two better than the others.

Table 3: The optimized rules of scoring four features for the optimized fuzzy classifier

Rules	Correct	Incorrect
If the mean of channel 2 is less than 0.64	+1	-1
If the mean of channel 4 is more than 1.36	+1	-1
If the maximum of channel 2 is less than 0.97	+1	-1
If the maximum of channel 4 is more than 0.96	+1	-1

Table 4: Accuracy of predicting each movement for each subject using an optimized fuzzy classifier

Subject	Total%	Abduction%	Grasping%	Pinching%
#1	87.50	80.21	96.88	71.88
#2	68.75	31.25	81.25	93.75
#3	79.17	56.25	84.38	96.88
#4	62.50	100	81.25	6.25
#5	76.04	62.50	90.63	75
#6	50	37.50	28.13	84.38
#7	71.88	71.88	78.13	65.63
#8	62.50	28.13	62.50	96.88
#9	52.08	28.13	46.88	81.25
#10	90.63	90.63	87.50	93.75
#11	72.92	53.13	68.75	96.88
#12	76.04	65.63	68.75	93.75
#13	90.63	100	75	96.88
#14	89.58	90.63	78.13	100
#15	80.21	75	71.88	93.75

Table 5: Accuracy of predicting each movement for each subject using the W-KNN algorithm

Subject	Total%	Abduction%	Grasping%	Pinching%
#1	91.67	90.63	100	84.38
#2	92.71	87.5	96.88	93.75
#3	91.67	84.38	96.88	93.75
#4	90.63	100	87.5	84.38
#5	94.79	93.75	96.88	93.75
#6	84.38	78.13	78.13	96.88
#7	83.33	81.25	96.88	71.88
#8	78.13	65.63	71.88	96.88
#9	83.33	62.5	93.75	93.75
#10	97.92	100	100	93.75
#11	91.67	84.38	93.75	96.88
#12	87.5	78.13	87.5	96.88
#13	100	100	100	100
#14	97.92	93.75	100	100
#15	88.54	81.25	93.75	90.63

For the same reason, channel four is the best detector of finger abduction movements as it covers the Extensor Indicis, Extensor Pollicis Longus, and Abductor Pollicis Longus muscles. Dorsal Interossei and Adductor Pollicis muscles are the main finger abductors, but their origin and location are far from all four channels. Considering that most of the active muscles are located at the areas under the control of channels

#2 and 4 during the tests performed, the results obtained from two channels (channels #2 and #4) should not be much different in comparison to the results obtained from three and four channels (either or both of channel #1 and #3 included). The W-KNN algorithm, the most effective classifier, was used to investigate how the two channels (1 and 3) affected classification accuracy. When the data from channel #1 was added to the analysis, the accuracy was 84.8%; however, if the data from channel #3 was added, the accuracy was 85.8%. Finally, we added data from both channels #1 and #3 to the previous data of channels #2 and #4 and gained classification accuracy of 86.7% showing a 3.6% improvement in comparison to using only two channels #2 and #4.

4. Conclusion

Prosthesis and exoskeletons are becoming more common in patients, and the need for their improvement is felt more than ever. The electromechanical delay caused by transporting signals is one of the existing issues. The main purpose of this work was to decrease the delay time by predicting movements before they became completed. In this study, our goal was to figure out how to anticipate hand movements. To do this, we investigated the signals that happen just before someone begins moving their hand. We specifically concentrated on a period of about 500 milliseconds from when a signal is triggered by a photodiode to when the subject actually starts moving his/her hand. By studying this short time frame, we aimed to comprehend the lead-up to a hand movement, which can be used in rehabilitation devices. This made it easier for us to understand how our brain signals and senses work together to produce a deliberate movement. This work was done by extracting features from four channels, and ultimately using only two of them for classification with three methods (fuzzy, optimized fuzzy, and W-KNN classification).

By using only channel #1 for W-KNN classification, the prediction accuracy reached 84.8%. With the addition of channel #3, the accuracy increased to 85.8%. Finally, by incorporating data from all four channels, the classification accuracy improved to 86.7%, representing a 3.6% increase compared to using only channels #1 and #3. While these results are better than those with two channels, using just channels #1 and #3 would be sufficient when considering the time and computational cost of the process. Even with four channels, the number of electrodes is fewer than in other related studies, without significantly reducing prediction accuracy. Additionally, fewer electrodes help minimize time-related expenses. Therefore, this study, compared to previous works with more channels, achieved faster movement prediction, reduced computational costs, and enhanced functionality for prosthesis and exoskeleton applications. Notably, this work focused on prediction rather than recognition, as it analyzed signals before the onset of motion.

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