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EMG-based hand gesture classification using Myo Armband with feedforward neural network

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ABSTRACT

This paper presents the development of an electromyography (EMG)-based hand gesture identification system for remote-controlled applications. Even though the Myo Armband is no longer commercially supported, the research discusses its use in EMG data collecting. Open-source libraries were utilized to capture EMG data from this device to solve this problem. Using the developed data acquisition platform, data was collected from 30 participants who performed three (3) gestures - a fist, an open hand, and a pinch. The energy spectral density (ESD) and power ratio (pRatio) were extracted to describe gesture-specific patterns. A feedforward neural network (FFNN) was implemented for classification, initially configured with 10 hidden neurons and later optimized to 40 neurons to improve the performance. The box plot analysis showed channels CH1, CH4, CH5, and CH7 as the most significant for enhancing classification accuracy. The optimized FFNN achieved 80% and 70% for the training and testing accuracies, respectively. However, the results suggest that implementing a systematic protocol during data acquisition to reduce signal overlap between movements could improve classification accuracy. In conclusion, the study successfully developed an open-source EMG data acquisition platform for MYO Armband and demonstrated acceptable hand gesture recognition using an optimized FFNN.

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1. INTRODUCTION

Electromyography (EMG) signals play a crucial role in human-computer interaction, particularly in applications such as prosthetics, robotics, and virtual reality (VR) [1]. These signals provide a non-invasive means of capturing muscle activity, which can be leveraged for hand gesture recognition. Hand gesture classification using EMG signals has been widely explored for various control applications, including teleoperation robots, rehabilitation devices, and virtual interfaces [2]-[4]. However, accurately classifying EMG signals remains challenging due to signal variability, noise interference, and the limitations of available hardware [5]-[7].

Teleoperation robots interpret EMG signals using multiple approaches, including rule-based expert systems, pattern recognition, and machine learning techniques. Traditional methods such as support vector machines (SVM) [8], [9] and linear discriminant analysis (LDA) [10], [11] have demonstrated success in gesture classification, but they often lack the robustness needed for real-time applications [12]. More recently, deep learning models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks have been employed for gesture recognition tasks, showing improved performance due to their ability to extract temporal and spatial features from EMG signals [13], [14]. However, these models require high computational resources and extensive training datasets [15].

Feedforward neural networks (FFNNs) present a computationally efficient alternative with competitive classification accuracy [16]. They have been widely used in gesture recognition tasks due to their simple architecture and ability to generalize well with limited data. In this study, we investigate the classification performance of an FFNN-based approach using EMG signals acquired from the Myo Armband, an 8-channel EMG sensor. Despite its discontinuation, the Myo Armband remains a widely used device for EMG research, supported by open-source tools that enable continued experimentation and validation [17].

Feature selection plays a crucial role in improving the performance of EMG-based gesture classification systems. Various techniques, such as principal component analysis (PCA) [18], correlation analysis [19], and box plot analysis [20], have been used to identify the most relevant features for classification. In this study, we employ box plot analysis to determine the most significant EMG channels that contribute to improved gesture classification accuracy [21]. By refining the input feature set, we aim to enhance the robustness of the classification model while minimizing computational complexity.

The key objective of this study is to develop an EMG-based hand gesture classification system using an optimized FFNN while evaluating the effectiveness of different feature selection techniques in improving classification performance. Additionally, it aims to analyze the impact of various EMG signal processing methods on gesture recognition accuracy and provide a comprehensive comparison of FFNN with other neural network models in the literature. By addressing these objectives, this study contributes to the ongoing development of robust and efficient EMG-based gesture recognition systems, with potential applications in assistive technologies, rehabilitation, and human-computer interaction.

This paper is organized as follows: section 2 details the methodology, including data acquisition, feature extraction, and neural network implementation. Section 3 presents the results and discussion, highlighting the key findings and comparing them with previous studies. Section 4 concludes the study with insights into future research directions.

2. METHOD

2.1. Data collection

The study utilizes an 8-channel Myo Armband to collect EMG signals from the forearm, as illustrated in Figure 1. The Myo Armband, a widely used wearable sensor, measures the electrical activity generated by skeletal muscles and provides a convenient method for non-invasive signal acquisition [22]. To ensure compatibility with standard machine learning pipelines, an open-source data acquisition library was employed for data collection and preprocessing.

Data were collected from 30 participants, each instructed to perform three predefined hand gestures: a fist, an open hand, and a pinch. Standardized instructions were provided to all participants to maintain consistency throughout the data collection process. The Myo Armband was positioned on the lower forearm, where most of the muscles responsible for finger movements are located, ensuring optimal signal capture [23]. Each participant performed multiple repetitions of each gesture under controlled conditions, with sufficient rest intervals between trials to minimize signal overlap and contamination. The recorded EMG data were then stored for subsequent analysis, including feature extraction and classification.

Figure 1. Myo Armband with 8-channel muscle sensors

2.2. Signal processing and feature selection

To enhance classification performance, the EMG signals underwent a series of preprocessing steps, including normalization, noise filtering using a band-pass filter (20-450 Hz), and artifact removal to ensure signal integrity. Feature extraction was then performed to capture relevant muscle activity characteristics. Two primary features were derived from the signals: energy spectral density (ESD) and power ratio (pRatio) [24]. ESD represents the power distribution across different frequencies, effectively highlighting patterns of muscle activation. Meanwhile, pRatio measures the proportion of signal energy in distinct frequency bands, providing additional insight into muscle activity variations. To further optimize classification accuracy, box plot analysis was conducted to identify the most significant EMG channels for gesture recognition. The analysis revealed that channels CH1, CH4, CH5, and CH7 exhibited the highest discriminative power, making them the most suitable for further processing and classification. Figure 2 shows an example of the box plot analysis used in this study.

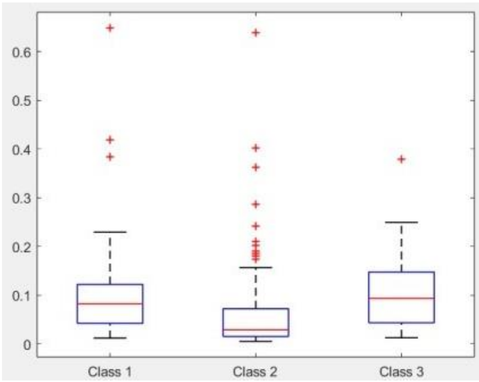


Figure 2. An example of a box plot used to select features for accurate classification

2.3. Feedforward neural network implementation

Figure 3 shows the block diagram of an FFNN. A FFNN was implemented to classify EMG-based hand gestures, initially configured with a single hidden layer containing 10 neurons as shown in Figure 3(a). To enhance performance, an optimised model was later developed with two hidden layers, each comprising 20 neurons, resulting in a total of 40 neurons as shown in Figure 3(b). The rectified linear unit (ReLU) activation function was applied to the hidden layers to improve learning efficiency, while the Softmax activation function was used in the output layer for multi-class classification. The model was trained using the backpropagation algorithm with the Adam optimizer, which is well-suited for handling non-stationary signals such as EMG data.

To assess classification performance, key evaluation metrics, including accuracy, precision, recall, and F1-score, were employed. Initially, the FFNN was trained using only the ESD feature with 10 hidden neurons. However, this configuration yielded suboptimal results, prompting further refinement. The model was subsequently optimized by increasing the number of neurons to 40 and incorporating both ESD and pRatio features to improve classification accuracy. To ensure a robust evaluation, the dataset was divided into 70% for training and 30% for testing, allowing the model to generalize effectively across unseen data.

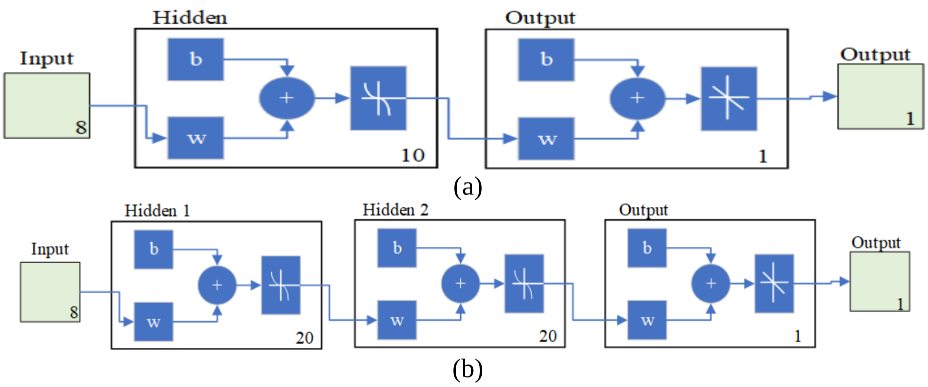


Figure 3. Configuration of FFNN for (a) initial setup with 10 neurons and (b) optimized setup with 40 hidden neurons

2.4. Performance analysis

A confusion matrix is employed to analyze the performance of the developed FFNN for hand gesture classification and evaluate this network's training, testing, and validation outcomes. It is a tabular representation utilized to evaluate the efficacy of a classification model by comparing the predicted and the actual classes. This tool is essential in machine learning for assessing model accuracy by offering a comprehensive analysis of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). It facilitates the visualization of an algorithm's performance, particularly in supervised learning, where the model's predictions are compared with the actual ground truth. The formulas for computing the true positive rate (TPR) or recall, true negative rate (TNR) or precision, accuracy, and F1-score are presented in (1) to (4) [25]. Accuracy determines the network's overall performance in correctly predicting hand gestures.

$$TPR\ (Recall) = \frac{TP}{TP+FN} \tag{1}$$

$$TNR\ (Precision) = \frac{TN}{TN+FP} \tag{2}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

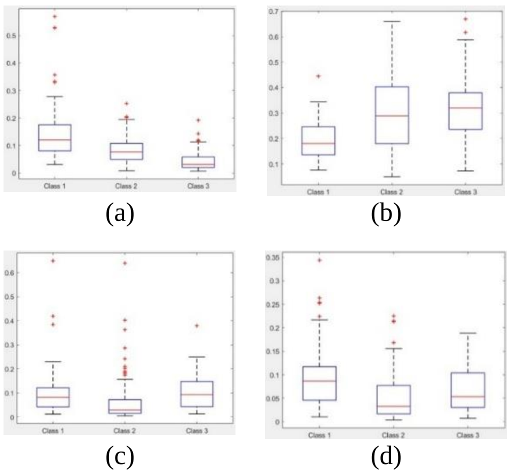
$$F1 = 2 \times \frac{Precision \times Recall}{Precision+Recall} \tag{4}$$

3. RESULTS AND DISCUSSION

This section presents the results of feature selection using box plot analysis and the performance evaluation of FFNN-based hand gesture classification. The discussion highlights key findings, compares them with prior studies, and analyzes their implications.

3.1. Box plot analysis for feature selection

To identify the most significant EMG channels for classification, a box plot analysis was conducted. The analysis was performed across all eight channels of the Myo Armband, and the results revealed that CH1, CH4, CH5, and CH7 exhibited the highest discriminative power. These channels demonstrated significant variations in muscle activity between different hand gestures, making them crucial for feature extraction and classification. Figure 4 illustrates the box plot analysis of these selected channels. Figure 4(a) represents CH1, where a clear difference in data distribution is observed among the three gesture classes. Figure 4(b) and Figure 4(c) (CH4 and CH5) show a wider interquartile range (IQR), signifying substantial variability in muscle activation. This characteristic improves their ability to distinguish between gestures. Figure 4(d) (CH7) exhibits a balanced IQR and a noticeable median shift across the three gesture classes, ensuring stable signal distribution. The remaining channels (CH2, CH3, CH6, and CH8) were excluded due to their lower statistical relevance in gesture differentiation. These results highlight the importance of feature selection in optimizing classification performance. By focusing on the most relevant EMG channels, the computational complexity is reduced while maintaining high classification accuracy.



(a) (b) (c) (d)

Figure 4. Box plot analysis of the most significant EMG channels (a) CH1, (b) CH4, (c) CH5, and (d) CH7, for FFNN-based hand gesture classification

3.2. Hand gesture classifications using FFNN

The initial classification experiment utilized only the ESD feature. The results in Table 1 show that using 10 hidden neurons led to suboptimal performance, particularly in recall and precision metrics. This limitation can be attributed to underfitting, where the model failed to capture the complex variations in EMG signals. When the number of hidden neurons was increased to 40, performance improved across all classes, with an average F1-score improvement of 21%. However, despite this enhancement, the model's ability to generalize across different gestures remained moderate, indicating the need for further feature optimization. The result of the optimized hand gesture classification using ESD and pRatio features is shown in Table 2.

Table 1. The performance of the hand gesture classification using 10 and 40 neurons for the ESD feature alone

Number of hidden neurons		Class 1 (Fist)		Class 2 (Open hand)		Class 3 (Pinch)		Class 4 (Disturbance)	
		10	40	10	40	10	40	10	40
PPV (precision)	Training	0.64	0.70	0.76	0.83	0.52	0.72	0.00	0.00
	Testing	0.53	0.80	0.75	0.87	0.20	0.53	0.00	0.00
	Validation	0.71	0.69	0.90	0.86	0.56	0.58	0.00	0.00
TPR (recall)	Training	0.82	0.96	0.51	0.60	0.78	0.82	0.00	0.00
	Testing	0.80	1.00	0.32	0.59	0.75	0.82	0.00	0.00
	Validation	1.00	1.00	0.43	0.55	0.91	0.78	0.00	0.00
F1-score	Training	0.72	0.81	0.61	0.69	0.62	0.77	0.00	0.00
	Testing	0.64	0.89	0.45	0.70	0.32	0.64	0.00	0.00
	Validation	0.83	0.81	0.58	0.67	0.69	0.67	0.00	0.00
Accuracy	Training	0.84	0.89	0.65	0.76	0.81	0.86	1.00	0.99
	Testing	0.79	0.99	0.48	0.94	0.69	0.95	1.00	0.99
	Validation	0.90	0.97	0.69	0.94	0.79	0.96	1.00	1.00

Table 2. The performance of the optimized hand gesture classification using 10 and 40 neurons for the ESD and pRatio features

Number of hidden neurons		Class 1 (Fist)		Class 2 (Open hand)		Class 3 (Pinch)		Class 4 (Disturbance)	
		10	40	10	40	10	40	10	40
PPV (precision)	Training	0.86	0.76	0.80	0.86	0.67	0.70	0.00	0.00
	Testing	0.80	0.87	0.87	0.92	0.53	0.57	0.00	0.00
	Validation	0.76	0.83	0.94	0.80	0.33	0.80	0.00	0.00
TPR (recall)	Training	0.96	0.98	0.62	0.62	0.80	0.85	0.00	0.00
	Testing	1.00	1.00	0.59	0.63	0.82	0.89	0.00	0.00
	Validation	1.00	0.83	0.63	0.75	0.75	0.86	0.00	0.00
F1-score	Training	0.91	0.85	0.70	0.72	0.73	0.77	0.00	0.00
	Testing	0.89	0.93	0.70	0.75	0.64	0.70	0.00	0.00
	Validation	0.87	0.83	0.75	0.77	0.46	0.83	0.00	0.00
Accuracy	Training	0.94	0.91	0.78	0.78	0.82	0.86	1.00	0.99
	Testing	0.95	0.95	0.74	0.81	0.76	0.83	1.00	1.00
	Validation	0.90	0.90	0.76	0.83	0.83	0.88	0.98	1.00

According to Table 2, the overall result of hand gesture classification is higher than the previous. However, the result for class 3 (Pinch) is still challenging; validation F1-score languished at 0.46, reflecting underfitting on this subtler movement. The unbalanced data for training, testing and validation data contributed to this trade-off when the data window was not captured accurately and consistently.

The results of this study demonstrate that the combination of ESD and pRatio features significantly enhances hand gesture classification accuracy when using a FFNN model. Compared to prior research that primarily utilized CNNs and LSTM models for gesture recognition, this study highlights the effectiveness of FFNNs as a lightweight and computationally efficient alternative. While CNN-based models typically achieve higher accuracy, they come with increased computational complexity and longer training times. Similarly, LSTM models excel in capturing temporal dependencies in sequential data, but they require larger datasets and greater computational resources, making them less suitable for applications with limited data availability. In contrast, the FFNN model used in this study offers competitive classification performance while maintaining faster training times and lower computational requirements, making it a practical choice for real-time applications.

Despite its promising results, this study has some limitations. One key challenge is signal contamination caused by overlapping gestures, which can reduce classification accuracy. Additionally, the limited dataset size may impact the model's ability to generalize across different users and environments. Another limitation is the exclusion of additional EMG feature sets, such as waveform length and signal entropy, which could potentially improve classification accuracy by capturing more complex signal characteristics.

To address these limitations, future research should focus on enhancing feature selection techniques, such as PCA, to further refine the input data and improve classification performance. Additionally, exploring hybrid models that combine FFNNs with CNN or LSTM architectures could leverage the strengths of each approach for improved accuracy. Finally, expanding the dataset by including a larger pool of participants and a wider range of hand gestures would enhance model generalization and robustness in practical applications.

4. CONCLUSION

This study successfully addressed the challenges posed by the discontinuation of the Myo Armband by developing an effective method for capturing and classifying EMG signals for remote-controlled applications. By utilizing open-source tools for EMG data acquisition, implementing ESD and pRatio for feature extraction, and employing a FFNN for classification, the project achieved training accuracies of approximately 80% and testing/validation accuracies above 70%. The optimization of the FFNN, focusing on significant channels identified through box plot analysis, proved effective in improving classification performance. Future research should explore the integration of additional neural network architectures, such as CNNs or LSTMs, and include the data acquisition protocol. This will expand the dataset to include a wider variety of gestures and participants, potentially improving the model's generalizability.

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AUTHOR CONTRIBUTIONS STATEMENT

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Sofea Anastasia Mohd Said			✓	✓	✓	✓	✓	✓	✓					
Norashikin M. Thamrin	✓	✓		✓		✓	✓			✓		✓	✓	
Megat Syahirul Amin Megat Ali	✓	✓	✓	✓			✓					✓		
Mohamad Fahmi Hussin				✓						✓				
Roslina Mohamad				✓						✓				

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The research related to human use has been complied with all the relevant national regulations and institutional policies in accordance with the tenets of the Helsinki Declaration and has been approved by the authors' institutional review board.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, [Norashikin]. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

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