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EMG-Based Arm Motion Gesture Classification

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Abstract. This study presents a forearm gesture classification method based on electromyography (EMG), recurrent neural network (RNN), and a two-layer Long Short-Term Memory (LSTM). The gesture data of one experimental subject was collected experimentally. After data preprocessing such as filtering and reshaping processes, an RNN model was trained for automatic movement feature extraction and classification. The experimental result shows that when the selected muscle pair is biceps brachii and extensor carpi radialis longus, the classification accuracy of the model achieves the highest classification accuracy of 97.5%, which is significantly more accurate than the other three experimented muscle pairs. This study verifies and confirms that the effectiveness of movement classification based on EMG is accurate enough for the appropriate pair of muscles, and provides a direction for future optimization and applications, such as enabling touchless and gesture-based control through muscle signals and improving the ability of complex gesture recognition.

Keywords: Gesture, Electromyography (EMG), Recurrent Neural Network (RNN), Classification

1. Introduction

Emerging brain-computer interface (BMI) technology allows direct communication between the human nervous system and external devices. It has the potential to make interaction with machines more convenient, efficient, and safe. Among various sensing technologies, electromyography (EMG) has become one of the most significant tools in brain-computer interfaces. EMG is a non-invasive technique used to analyze the electrical activities of skeletal muscles, it is quite convenient that only needs to attach few electrode sensors to capture and generate the electrical signal. The measurement of EMG signals has wide applications in various fields, including disease diagnosis and rehabilitation in clinical practices [1], and control of exoskeletons for people with special needs to perform tasks naturally [2-4]; and also enhanced human capabilities [5], for example the operation of intelligent household furniture [6], and enabling hands-free or touchless control for answering calls [7]. Due to the activation speed of EMG signals is faster than body movements, they

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help achieve more efficient human-computer interaction, thereby improving the convenience, ease, and safety of operation.

Although there have been significant advancements in EMG gesture classification, due to factors such as individual differences, electrode placement variations, and muscle fatigue, achieving robust, accurate, and real-time gesture recognition remains challenging [8]. Addressing these issues and challenges is more likely to enhance the universality of BMI systems in assistive and rehabilitation applications and enable them to have a wider range of applications.

In this paper, we combine EMG, RNN, and LSTM to make an EMG-based gesture classification system that detects electrical signals from arm muscles to identify 4 specific movements to resolve some of the current issues in human-machine interactions. Specifically, by recording and collecting electrical signals from participants, EMG data is preprocessed and classified to identify muscle activity by using a recurrent neural network (RNN), which learns temporal information of EMG graphs. The system achieves reliable recognition of these 4 common gestures in our real-time experiment. The classified movements can serve as intuitive control instructions for monitoring various devices, such as intelligent furniture and smart home systems [9], enabling more natural human–device interaction. This approach demonstrates the potential of EMG as a practical interface for everyday applications and also providing a foundation for integrating gesture-based control into diverse smart appliances.

2. Methodology

2.1. EMG data acquisition

EMG data was collected from a real gesture experiment by using an EMG Acquisition System. 2 recording channels were used for data collection, and each channel utilized a three-electrode configuration: the yellow one is the active electrode, the red one is the reference electrode, and the green one is the Ground electrode. We attached the yellow electrode to the most muscular part (the center of the muscle), the red electrode to the end of the muscle, and the green electrode to the protruding area of the bone near the muscle.

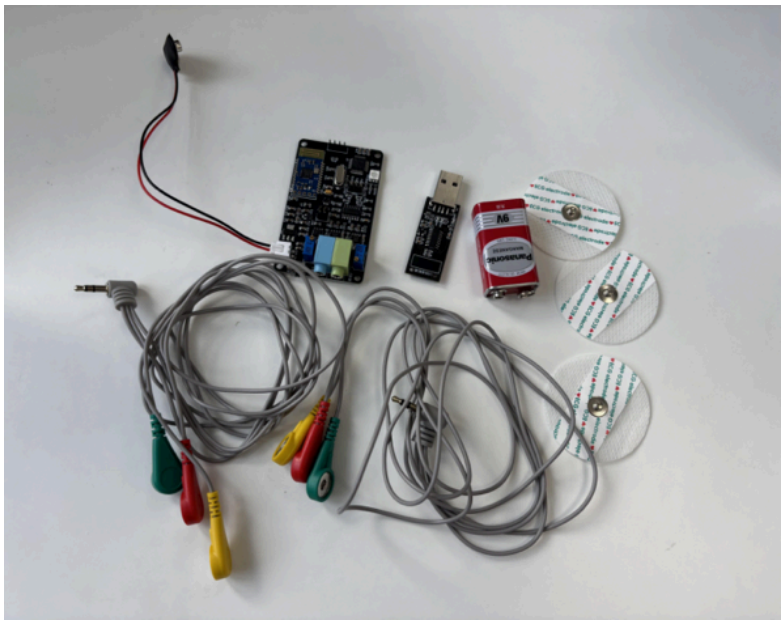

Figure 1. EMG system used [10]

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EMG data were obtained through experiments that used the EMG Acquisition System by testing 4 different gestures involving 1 subject. Each 2 gestures form a group, the first group of movement is elbow flexion followed by extension, and the second group of movement is forearm supination followed by pronation. These two groups of movement form a set. Each set underwent 10 test sessions, and in each session, both movements were repeated 10 times. Each movement lasted approximately 3 seconds, 30 seconds rest between each trial, and 5 minutes rest between each muscle pair. The sampling rate was 312 Hz, resulting in 936 samples per 3-second movement (312x3=936).

The arm muscles that are closer to the skin surface were identified using the anatomical diagrams of the arm muscles. They were biceps brachii muscle and triceps brachii muscle on the upper arm, and extensor carpi radialis longus muscle and flexor carpi ulnaris muscle on the forearm. Then, the electrodes were connected to the selected muscle groups. By connecting them to the system, it was discovered that there were signal fluctuations when the subjects performed specific actions, and this further confirms that the muscles tested in the experiment can be utilized.

These muscles were divided into two groups, and finally, four groups of muscles were selected as our experimental muscle samples for data collection. They are biceps brachii muscle with triceps brachii muscle, biceps brachii muscle with extensor carpi radialis longus muscle, biceps brachii muscle with flexor carpi ulnaris muscle, and triceps brachii muscle with extensor carpi radialis longus muscle. Electrodes were placed on targeted muscles:

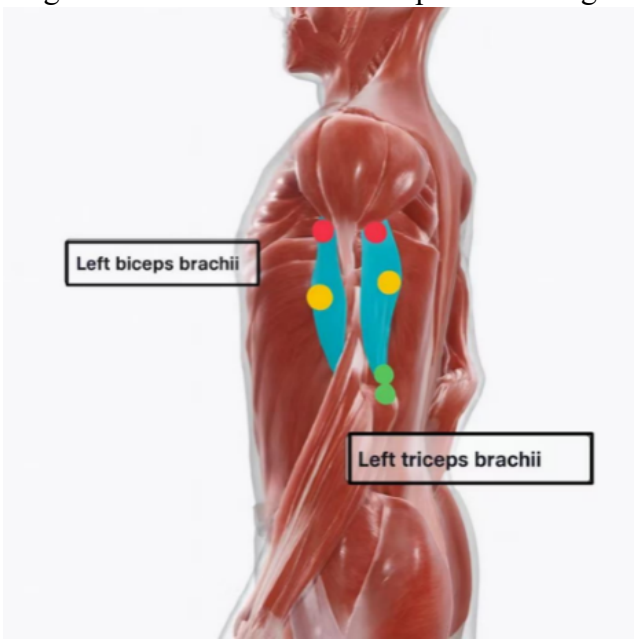

Figure 2. Electrode placement on biceps brachii & triceps brachii m

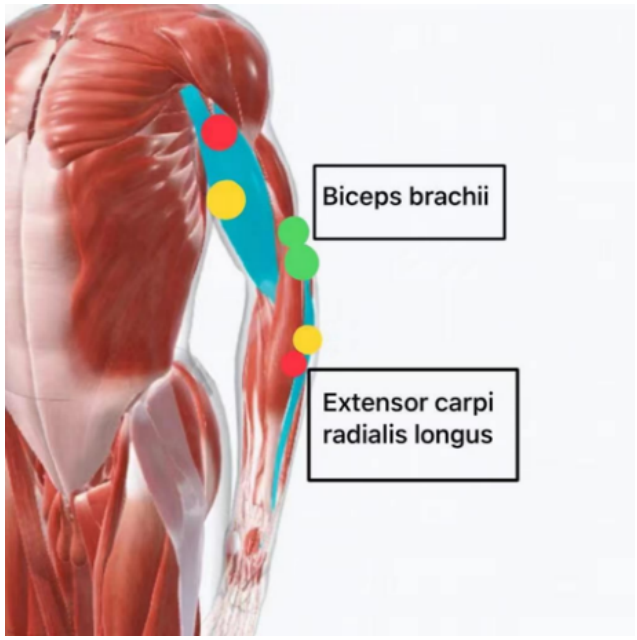

Figure 3. Electrode placement on biceps brachii & extensor carpi radialis longus m

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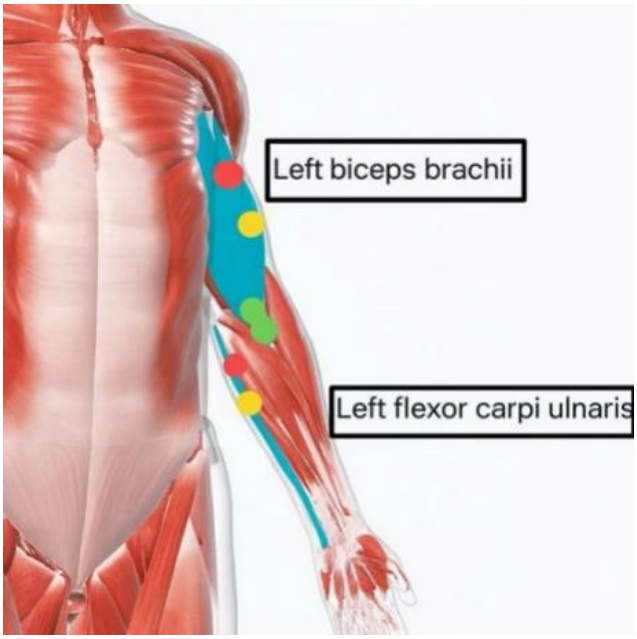

Figure 4. Electrode placement on biceps brachii & flexor carpi ulnaris m

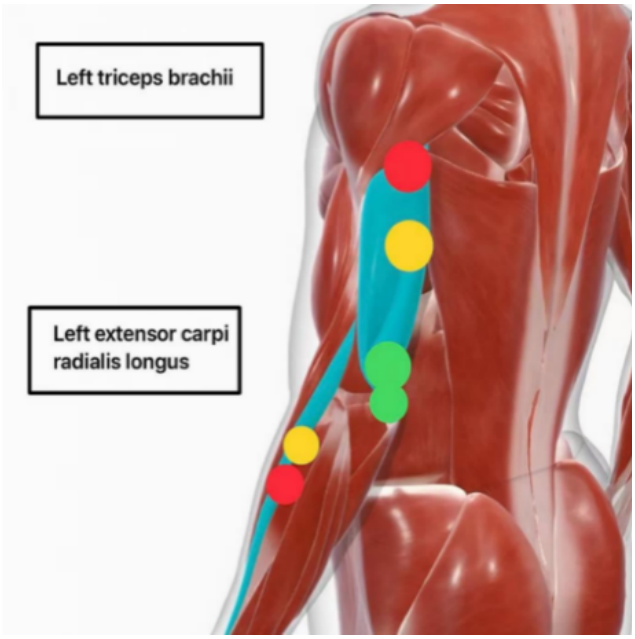

Figure 5. Electrode placement on triceps brachii & extensor carpi radialis longus m

Data acquisition as described above was repeated by the participant using each of the 4 electrode positionings. To evaluate and compare the effectiveness of different muscle group combinations, four independent RNN models were trained separately, each corresponding to one of the four muscle pairs. After getting the muscle group with the highest accuracy rate, a real-time experiment, which is for verifying the accuracy of the data, was conducted by repeating the data collection for this muscle group.

2.2. Data preprocessing

First, organize the processed EMG signals into individual data files. Each file contains a large number of complete 3-second recordings for repetitions of a specific movement, and data from every file is captured from both EMG channels. The EMG system recorded three fundamental time-domain features per channel at each sampling point: Raw signal value, signal power, and muscle strength. At each sampling point, the EMG system records three fundamental features: raw signal value, signal power and muscle strength. So, at any moment in each three second interval, these three features from both channel of the dual-channel EMG provides a data point with six features. To ensure the accuracy of the data, we performed strict checks. The sampling rate was 312 Hz, after multiple by 3 seconds, it is 936 rows of data. So only the files that passed as 936 rows are kept, by a 6-column matrix, which is calculated by 3 features per channel multiple by total of 2 channels, and any file containing missing values or wrong number of rows are removed. While verifying the data structure, originally it was 1 for elbow flexion-extension and 2 for forearm supination-pronation. Then we adjusted these labels, each label was subtracted by 1, so this they were converted into a binary classification system, which is 0 for elbow flexion-extension and 1 for forearm supination-pronation.

The processed and validated data (each with 936-time points x 6 features) is imported into tables that need to be restructured to conform to the RNN input data format. This procedure transforms the tabular EMG data into a regular three-dimensional data structure. The format is sample number ×

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1872 time points (the sampling frequency is 312 Hz, each action lasts 3 seconds, and each record contains 2 full movement cycles, 312Hz × 3 seconds × 2 cycles = 1872 time points) × 6 features. After adjustments, each individual action data segment becomes a proprietary matrix: one dimension is 1872 continuous time points, and the other is the six features corresponding to each time point, which means that the structure of each sample is (1872, 6). In addition, the previously standardized binary labels (0 for elbow flexion-extension, 1 for forearm supination-pronation) are retained and correctly matched to each sample, and are prepared for the final importation into the RNN model.

2.3. Model development and evaluation

2.3.1. Model architecture and training framework

For movement classification, we employed a recurrent neural network (RNN) built with long short-term memory (LSTM) units [11]. The network architecture features two continuous LSTM layers. The first layer contains 64 units and processes the input sequence and outputs the full sequence of its results over time. This output is then fed into the second LSTM layer, which has 32 units and condenses the sequential information into a single, fixed length summary vector for capturing the essential temporal patterns. Finally the summary vector passes through an output layer that uses a Softmax activation function, to produce the probability scores of our two designed moments. In this process, we trained each RNN model for four times, and each training was independent of others. By collecting EMG data from four different combination of muscles, each model can learn the unique muscular signals associated with a specific muscle group combination, so the model can form and improve its classification ability to those particular movement signals.

2.3.2. Assessment of classification performance

We conducted a quantitative evaluation of the prediction performance of each trained RNN model. The primary metric was the overall classification accuracy (the percentage of times of correctly classified movements across both types of movement). The performance metrics for each movement class were also examined: precision (positive predictive value), recall (sensitivity), and the F1 score (the harmonic mean of precision and recall). These metrics were calculated by comparing the model's predicted labels against the actual labels and counting the true positives (TP), false positives (FP), and false negatives (FN). We also used confusion matrices (a tabular layout that visualizes model performances by cross-tabulating actual classes against predicted classes) to get a clear visual picture of the classification results, and show exactly how many segments of each movement type were classified correctly or not. We also conducted statistical tests on these performance metrics to show the percentage probabilities of each index, so it is easier for better determine whether the differences observed in classification between the different muscle group configurations were meaningful, and whether a specific muscle pair is worth real-life applications.

NOTE: Precision and Recall were computed by the model and measured but are not reported or analyzed in this paper.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$Precision = \frac{TP}{TP+FN} \tag{2}$$

$$Recall = \frac{TP}{TP+FP} \tag{3}$$

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$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

2.3.3. Comparisons and analysis of muscle groups

In order to identify the most effective and accurate muscle pair for movement recognition, we systematically compared the results from four independently trained RNN models, each corresponding to a specific EMG recording configuration. The classification ability of it has successfully achieved a relatively stable and high performance within approximately 7 to 14 training epochs. This involved comparing models in pairs across different muscle group combinations, and looking closely at their test accuracy, confusion matrix patterns and classification metrics. These specific four muscle pairs evaluated were mentioned in the previous part (II. EMG DATA ACQUISITION), and this comprehensive comparison revealed clear performance differences between the configurations. By doing these, it is expected to find one or two muscle pairs where the performance of the combination is particularly good, then compare mainly on the Accuracy and F1 Score of the investigated muscle pairs to see whether the performance is good. These findings help to pinpoint the most discriminative and the best-performing muscle configuration, which could show a strong potential for application in real-time gesture classification and even in the real-life systems. During the follow-up real-time experiment, the muscle group with the best performance was tested by creating a confusion matrix through recording the TP, TN, FP, and FN values and calculating the accuracy, precision, recall, and F1 Score afterwards.

After determining the muscle pair with the best accuracy, the real-time experiment was conducted by repeating the measurement of that muscle pair. RNN was used to identify two different movement groups, and output a value of 0 or 1 in real time according to the changes in the gestures, 0 for elbow flexion-extension and 1 for forearm supination-pronation. A confusion matrix was used to record the accuracy of gesture recognition. If the subject bends or extends the arm, and the RNN shows 0, it indicates a correct recognition. Conversely, if the RNN shows 1, it means an incorrect recognition. If the subject rotates the forearm, an output of 1 from the RNN indicates a correct recognition, while an output of 0 indicates an incorrect recognition. Then record the number of correct and incorrect identifications of different movement groups and record them in the confusion matrix, and calculate the accuracy, precision, recall, and F1 score.

3. Result

3.1. Accuracy of trained classification models

The classification performance of different electrode placements was evaluated using confusion matrices for each muscle pair. Figures 1–4 present the confusion matrices for the four muscle pairs in Figures 2-6:

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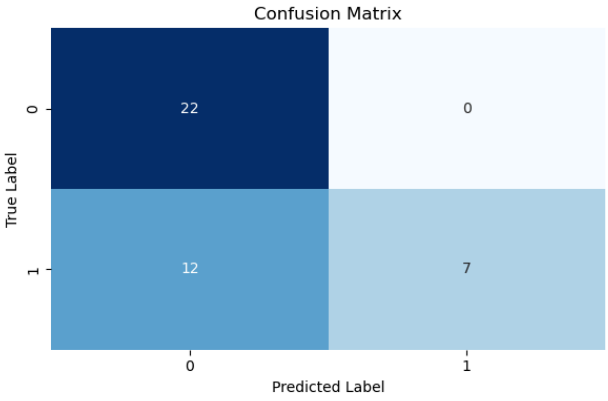

Figure 6. Confusion Matrix of Biceps brachii & Triceps brachii m

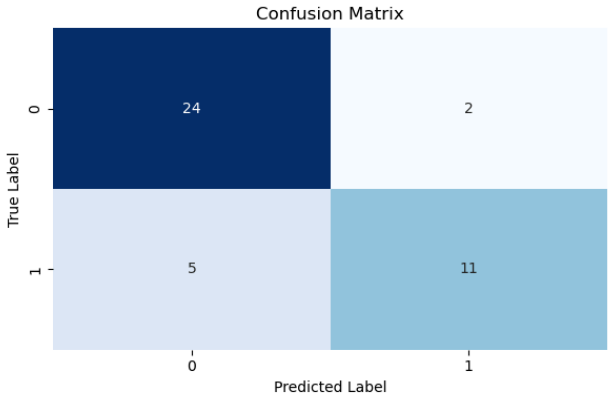

Figure 7. Confusion Matrix of Triceps brachii & Extensor carpi radialis longus m

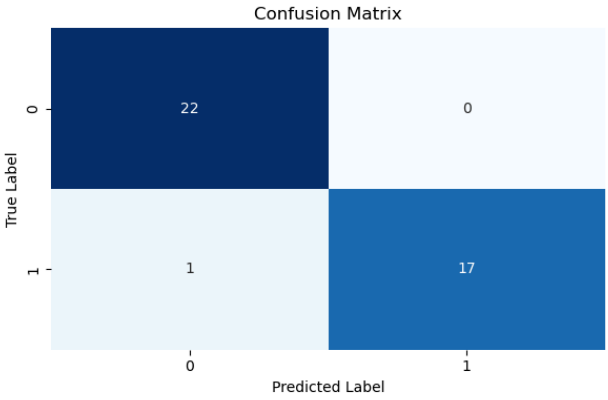

Figure 8. Confusion Matrix of Biceps brachii & Extensor carpi radialis longus m

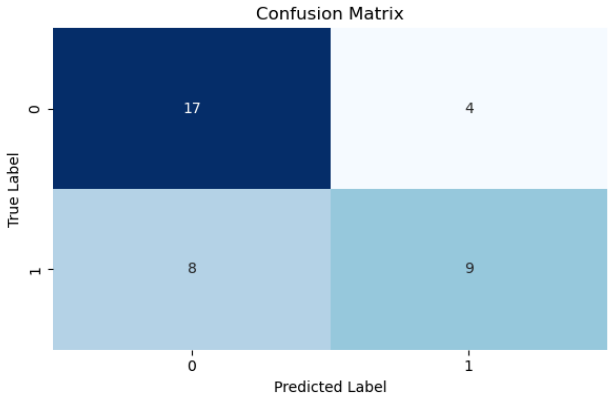

Figure 9. Confusion Matrix of Biceps brachii & Flexor carpi ulnaris m

In each confusion matrix, the values at positions (0,0) and (1,1) indicate the number of correctly classified samples, whereas positions (0,1) and (1,0) represent misclassifications. Among the four muscle pairings, Figure 3 (Biceps brachii & Extensor carpi radialis longus) shows the highest classification accuracy, with 22 and 17 correct predictions in each class and only one and zero misclassifications. This result indicates that this electrode placement provided the most accurate classification of arm motion gestures. Conversely, Figure 1 (Biceps brachii & Triceps brachii) shows the lowest accuracy, with more frequent misclassifications, indicating that this muscle pair was less effective for gesture recognition.

3.2. Comparative performance of electrode placements

To quantitatively compare the performance of each muscle pair, the accuracy and F1-scores were calculated.

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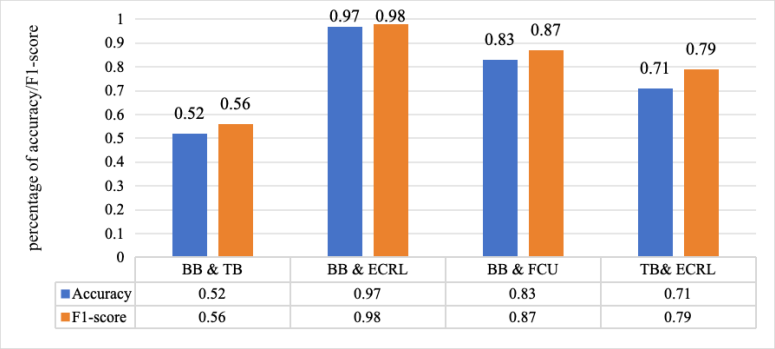

Figure 10. Accuracy and F1-scores for each muscle pair electrode placement

The Biceps brachii & Extensor carpi radialis longus pairing achieved the highest accuracy (0.97) and F1-score (0.98), whereas the Biceps brachii & Triceps brachii pairing performed the worst. These results indicate that electrode placement is a critical factor in EMG-based gesture classification and must be carefully considered to maximize classification performance.

3.3. Real-time EMG signal acquisition and classification

To validate the model under real-time conditions, the Biceps brachii & Extensor carpi radialis longus muscle pair was used for real-time EMG signal acquisition and classification because of the high accuracy performed.

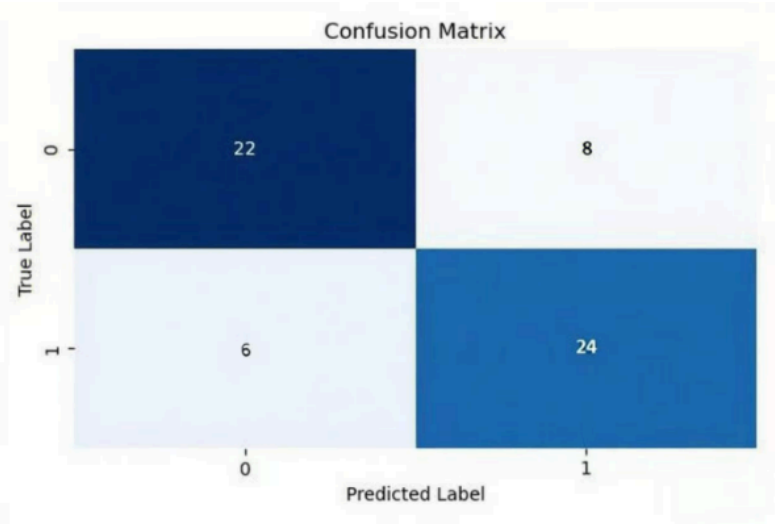

Figure 11. Confusion matrix of real-time EMG signal acquisition and classification using the Biceps brachii & Extensor carpi radialis longus muscle pair. Diagonal values interpret correct predictions, while off-diagonal values show misclassifications

Figure 11 shows the confusion matrix obtained from the real-time experiment. Out of all predictions, the model correctly classified 22 samples as class 0 and 24 samples as class 1, and 8 samples were misclassified as class 1 and 6 samples were misclassified as class 0.

These results indicate that the real-time classification performance remains high, consistent with the offline training results. Even though only a small number of misclassifications occurred, the majority of gestures were correctly recognized, suggesting that this electrode placement provides reliable and distinguishable EMG signals for practical real-time applications.

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4. Discussion

This investigation illustrates that muscle pair selection, preprocessing, and model design have a significant effect on EMG-based arm gesture classification. The Biceps Brachii and Extensor Carpi Radialis Longus muscle pair stood out in the performance in the data training part, with accuracy reaching as much as 97%, F1-score of 0.98. Proven that this muscle pair is the most effective placement. This finding implies that even with simple hardware setups and fewer electrodes can still provide high accuracy, which makes the system more practical. This coincides with the previous research results, where optimizing the electrode positions can enhance the reliability of classification, while maintaining performance without increasing complexity in the hardware [12,13]. Effective preprocessing and the use of an LSTM-based RNN further enhanced accuracy, consistent with studies reporting that deep recurrent models outperform traditional classifiers in handling sequential neuromuscular data [14]. The effective preprocessing (filtering, feature extraction, and standardization) together with the use of LSTM and RNN leads to a strong result, which successfully captures temporal patterns in the EMG signals. On the other hand, the Biceps brachii and Triceps brachii pair achieved only 52% accuracy, likely due to overlapping activation patterns, an issue noted in earlier studies highlighting crosstalk and co-contraction as barriers to EMG classification [15]. This solution highlights the significance of electrode placement. Ensuring high-quality, uniformly processed data is essential for fair comparison across different muscle pairs. Nevertheless, the limitations remain unresolved: a limited number of gestures were tested, and data were collected from a single subject, reducing generalizability. Future research should include expanding gesture set, including more diverse subjects, and exploring multimodal systems or attention-based models to further improve robustness [16]. In order to further enhance classification accuracy.

5. Conclusion

This study has illustrated that electrode placement has a crucial impact on the EMG signals when measuring arm movements. Through the RNN model, different muscle pair configurations were evaluated, and the biceps brachii and extensor carpi radialis longus pair had the most significant effect, and also maintaining strong performance in real-time experiments. In contrast, other muscle pairs failed to meet expectations, with accuracy rates being quite low. This highlights the importance of carefully placing electrodes to capture different muscle activation patterns. It emphasizes the influence of optimizing electrode configuration on achieving high classification performance, reducing hardware complexity, and promoting the development of efficient and user-friendly EMG-based gesture recognition systems. This work lays the foundation for future research, aiming to expand the gesture set and validate the model across different participants to further enhance the accuracy and robustness of real-time classification.

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SIN-LI TSENG, JIAYI LIU, YASHI WU, and PINQIAO WANG contributed equally to this work and should be considered co-first authors.

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References

[1] V. C. R, S. A. Gunagi, V. K. A, Shrinath Darur, and S. K. V, “Multi Channel Acquisition and Scope of Analysis of Surface EMG signals, ” 2020 IEEE International Conference for Innovation in Technology vol. 10, pp. 1–5, Nov. 2020, https: //ieeexplore.ieee.org/document/9298279

[2] [X. Zhang, Y. Qu, G. Zhang, Z. Wang, C. Chen, and X. Xu, “Review of sEMG for Exoskeleton Robots: Motion Intention Recognition Techniques and Applications, ” Sensors, vol. 25, no. 8, pp. 2448–2448, Apr. 2025, doi: https: //doi.org/10.3390/s25082448. Available: https: //www.mdpi.com/1424-8220/25/8/2448. [Accessed: Aug. 02, 2025]

[3] Rodrigues-Carvalho, J Marvin Fernández, A. J. del-Ama, F. O. Barroso, and J. C. Moreno, “Review of electromyography onset detection methods for real-time control of robotic exoskeletons, ” Journal of Neuroengineering and Rehabilitation, vol. 20, no. 1, Oct. 2023, doi: https: //doi.org/10.1186/s12984-023-01268-8

[4] P. Pestrikov, “Development of a Multi-Channel Measuring System for EMG Recording from Prevention Muscles, ” 2020 Moscow Workshop on Electronic and Networking Technologies (MWENT), pp. 1–4, Mar. 2020, doi: https: //doi.org/10.1109/mwent47943.2020.9067417.

[5] Rachana Bhaskaran Venugopal, T Rajalakshmi, A. Suresh, and S. Raj, “EMG based Signal to Control Home Appliances by Partially Paralyzed People, ” Jul. 2020, doi: https: //doi.org/10.1109/iccsp48568.2020.9182313.

[6] S. Fan, Y. Qian, S. Yang, and J. Qiu, “Fusion of EEG and EMG Signals for Home Automation Based on Convolutional Neural Networks with Portable devices, ” 2023 3rd International Conference on Electronic Information Engineering and Computer Science (EIECS), pp. 552–556, Sep. 2023, doi: https: //doi.org/10.1109/eiecs59936.2023.10435371.

[7] Sree Haran A et al., “Brain Computing Interface based Auto Calling Using Eye Blink Detection Algorithm, ” 2021 Fifth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), pp. 780–786, Nov. 2021, doi: https: //doi.org/10.1109/i-smac52330.2021.9640881.

[8] Z. Qing, Z. Lu, Y. Cai, and J. Wang, “Elements Influencing sEMG-Based Gesture Decoding: Muscle Fatigue, Forearm Angle and Acquisition Time, ” Sensors, vol. 21, no. 22, p. 7713, Nov. 2021, doi: https: //doi.org/10.3390/s21227713

[9] M. Nguyen, T. N. Gia and T. Westerlund, "EMG-based IoT System using Hand Gestures for Remote Control Applications, " 2021 IEEE 7th World Forum on Internet of Things (WF-IoT), New Orleans, LA, USA, 2021, pp. 911-912, doi: 10.1109/WF-IoT51360.2021.9595957.

[10] Xinweilai. EMG03 Dual-Channel EMG Sensor Kit for Wearable Devices. [Online]. Available: https: //e.tb.cn/h.h9zU3bD1iID9Eyx?tk=Ccr24WkYToN. Accessed: Jul. 21, 2025.

[11] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory, " in Neural Computation, vol. 9, no. 8, pp. 1735-1780, 15 Nov. 1997, doi: 10.1162/neco.1997.9.8.1735.

[12] Felici, Francesco, and Andrea Del Vecchio. “Surface Electromyography: What Limits Its Use in Exercise and Sport Physiology?” Frontiers in Neurology, vol. 11, 2020, p. 578504. https: //doi.org/10.3389/fneur.2020.578504

[13] Sun, Shuai, et al. “Application of Surface Electromyography in Exercise Fatigue.” Frontiers in Physiology, vol. 13, 2022, p. 9406287. https: //doi.org/10.3389/fphys.2022.9406287

[14] Haab, Philippe, et al. “The Role and Effectiveness of Surface Electromyography Feedback in Sports and Orthopedic Rehabilitation: A Systematic Review.” Exploration of Musculoskeletal Diseases, vol. 2, no. 2, 2024, pp. 100–120. https: //doi.org/10.37349/emd.2024.00065

[15] Subbu, Raj, et al. “The Practical Use of Surface Electromyography during Running: Evidence and Pitfalls.” Open Access Journal of Sports Medicine, vol. 6, 2015, pp. 191–199. https: //doi.org/10.2147/OAJSM.S77797 Al-Ayyad, Taleb, et al. “Electromyography Monitoring Systems in Rehabilitation: Current Trends and Future Directions.” Electronics, vol. 12, no. 7, 2023, p. 1520. https: //doi.org/10.3390/electronics12071520

[16] Al-Ayyad, Taleb, et al. “Electromyography Monitoring Systems in Rehabilitation: Current Trends and Future Directions.” Electronics, vol. 12, no. 7, 2023, p. 1520. https: //doi.org/10.3390/electronics12071520