

EMG-Based Hand Gesture Recognition Using Interpretable Deep Learning for Prostheses

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ABSTRACT

This study proposes an EMG-based hand gesture recognition method for adaptive prosthesis applications using interpretable deep learning. The proposed method utilizes EMG (electromyography) signals obtained from arm muscles to identify various hand movements performed by prosthesis users. By using a deep learning architecture, the developed model can classify hand movements with high accuracy. This approach also integrates model interpretability through saliency map visualization techniques, which allows understanding of the key features used by the network to make decisions. EMG datasets collected from several subjects were trained to recognize hand gestures such as gripping, grasping, and waving, and were complemented with signal processing to reduce noise and improve data quality. Evaluation results show that the proposed deep learning model achieves classification accuracy of up to 95%, with a relatively low time-to-decision, making it suitable for prosthesis applications that require fast and accurate responses. The results of this study have the potential to improve prosthesis performance with smoother and more responsive control, as well as provide new insights for the development of biomedical signal-based prosthetic devices.



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INTRODUCTION

Electromyography (EMG)-based hand gesture recognition has developed rapidly in recent years, particularly in adaptive prosthesis applications. Adaptive prostheses that can accurately respond to user commands offer significant potential for improving the quality of life for individuals with physical limitations, particularly those requiring hand prostheses. EMG signals, generated by the electrical activity of muscles, are the primary data source used to detect and recognize muscle movements associated with human hand movements. The use of EMG signals in hand gesture recognition allows for more intuitive and natural control of prostheses, with applications across a wide range of activities such as grasping, gripping, or even other complex movements. However, although previous research has shown significant progress in EMG-based hand gesture recognition, major challenges remain in terms of system accuracy and response speed. EMG signal quality is often affected by various factors, including noise, inter-individual physiological variability, and measurement conditions, which can reduce system reliability. Therefore, more robust pattern recognition techniques are needed that can adapt to different user characteristics. One promising approach is the use of deep learning, which can handle non-linear and complex data more

efficiently and accurately than traditional techniques. In this study, we propose an interpretable deep learning approach for recognizing hand gestures based on EMG signals. This approach leverages a deep learning model trained to recognize various hand gestures and integrates interpretability techniques to understand the factors influencing the model's decision-making. A key aspect of this approach is the visualization of saliency maps, which allow us to see which parts of the EMG signal the model uses for classification. This approach is expected to achieve high-accuracy hand gesture recognition, fast response speed, and the ability to provide clearer and more understandable feedback to prosthesis users.

This research aims to explore the use of deep learning to improve the accuracy of EMG-based hand gesture recognition and to demonstrate how interpretability techniques can help improve the understanding of the model's decisions. We will also evaluate the model's performance using EMG datasets collected from various subjects to ensure that the solution can be adapted to a variety of physiological conditions and user configurations. With this approach, we hope to contribute to the development of more responsive and intuitive adaptive prostheses, as well as pave the way for further research in the field of biomedical signal-based human-computer interaction.

METHODS

In this study, electromyography (EMG) data collection was performed using surface EMG sensors placed on forearm muscles, such as the flexor and extensor muscles, to record signals generated during hand movements. Each conversation involved a series of specific hand movements, such as gripping, grasping, and waving, recorded at a sampling frequency of 1000 Hz. Prior to analysis, the EMG data were preprocessed using a bandpass filter between 20–500 Hz to remove noise, then divided into small segments with a duration of 250 ms. Each segment was then normalized using the mean and standard deviation to reduce differences between subjects and testing sessions, ensuring that the model can perform consistently across conditions.

The deep learning model used for EMG-based hand gesture recognition is a Convolutional Neural Network (CNN). CNN was chosen for its ability to capture local spatial features in time-series signal data. This model consists of three convolutional layers followed by a pooling layer to reduce the data dimensionality, and two fully connected layers at the end for classification. The ReLU activation function is used in each convolutional layer to provide non-linear capabilities to the model, while the softmax function is used in the output layer to generate hand gesture class predictions. As part of model interpretability, a saliency map technique was applied to understand which parts of the EMG signal most influence the model's classification decisions. Saliency maps are calculated by calculating the gradient of the model's output relative to the input for each hand movement class. Visualizing these saliency maps allows us to identify important features in the EMG signal used by the model to make decisions, as well as helping to reveal the decision-making process occurring within the deep learning model. This model was trained using a cross-entropy loss function for multi-class classification, using a customized Adam optimizer to accelerate convergence. Early stopping was applied during the training process to prevent overfitting. The model was trained for 50 epochs with a batch size of 32, and the dataset was split into

70% for training and 30% for testing. Model performance was evaluated using accuracy, precision, recall, and F1-score metrics. To ensure more robust results, k-fold cross-validation with $k = 5$ was performed on the testing dataset.

For comparison, several classical methods such as Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) were also applied to the processed data. Statistical features such as mean, variance, skewness, and kurtosis were extracted from the EMG signals for use in training the SVM and KNN models. Performance comparisons were conducted to assess whether the deep learning models provide significant improvements in classification accuracy and generalization ability compared to classical methods. After the model was trained and evaluated, an adaptive prosthetic system based on the model's predictions was implemented in an EMG-based hand prosthesis. This system connects body-mounted EMG sensors to the prosthesis's motors, enabling more precise and responsive hand movements to the received signals. Prosthetic control is based on the model's predicted movements, allowing the prosthesis to adapt to the user's activities in real time. The proposed method aims to improve EMG-based hand gesture recognition for adaptive prostheses using an interpretable deep learning model. Through the use of interpretability techniques such as saliency maps, this research not only focuses on improving classification accuracy but also provides a better understanding of how the model makes decisions, which is crucial in prosthetic applications.

RESULTS AND DISCUSSION

In this experiment, the proposed deep learning model was evaluated using EMG datasets collected from various subjects to classify various hand gestures, such as gripping, grasping, and waving. The evaluation results showed that the Convolutional Neural Network (CNN) model used was able to achieve high classification accuracy, with an average accuracy of 95% on the test dataset, indicating that this deep learning model is effective in recognizing hand gestures based on EMG signals.

Performance Comparison with Classical Methods

To assess the performance of deep learning models compared to classical methods, we compared the classification results of CNN models with Support Vector Machine (SVM) and K-Nearest Neighbors (KNN). Both classical methods are trained on statistical features extracted from EMG signals, such as mean, variance, skewness, and kurtosis. The results show that the CNN model outperforms SVM and KNN methods in terms of accuracy, precision, recall, and F1-score, with significant improvements, especially in terms of generalization ability and recognition of more complex gestures.

Table 1. Model Performance Comparison

Model	Accuracy (%)	Precision	Recall	F1-Score
CNN	95	94.7	95.3	94.9
SVM	87	85.6	86.8	86.2

KNN	82	80.1	81.5	80.8
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Table 1 shows that the CNN model outperforms SVM and KNN in all evaluation metrics, confirming its effectiveness in classifying hand movements using EMG signal data.

Model Interpretability with Saliency Maps

One of the key contributions of this research is the use of saliency maps to improve the model's interpretability. Using saliency maps, we were able to identify key parts of the EMG signal used by the model to make decisions. For example, for a gripping motion, the saliency maps showed that the model placed greater emphasis on flexor muscle activity, while for a waving motion, the model placed greater emphasis on extensor muscles. This visualization allows researchers and users to better understand how the model recognizes hand movements, which is crucial for increasing the trustworthiness of EMG-based prosthetic systems.

Figure 1 shows an example of a saliency map for a gripping motion. The lighter areas indicate the areas of the EMG signal that are most influential in the classification decision.

Inference Time and Response Speed

The system is optimized to provide a low inference speed for use in prosthetic applications requiring real-time responses. The proposed deep learning model demonstrates an average inference time of 15 ms for a single EMG signal input, which is fast enough for use in adaptive prosthetic control. This time is sufficient to ensure that the system can provide accurate and fast responses to various hand movements performed by the prosthesis user. This inference speed makes the system suitable for applications requiring real-time control without disruptive delays.

Evaluation of Adaptive Prosthesis Systems

After the model was developed, the adaptive prosthesis system was tested with hardware equipped with EMG sensors and motors to perform hand movements according to the received signals. The system was able to adapt the prosthesis's movements to the user's activities in real time, with consistent gesture recognition accuracy and no tracking failures. In trials, the adaptive prosthesis was able to effectively recognize gestures such as gripping and grasping with rapid response, and transition between movements smoothly. The prosthesis user was able to control the prosthesis in a more natural and intuitive manner, making the system easier to use in everyday life.

Discussion

The results of this study demonstrate that the use of deep learning in EMG-based hand gesture recognition is highly effective, especially with the use of saliency maps that improve model interpretability. The proposed CNN model not only excels in terms of

classification accuracy but also provides deeper insights into how the model makes decisions, which is crucial for medical applications such as prostheses. Comparisons with classical methods such as SVM and KNN show that CNN is better able to handle the complexity and variability of EMG data and can provide better performance in hand gesture recognition.

However, while this deep learning model is highly effective, it faces several challenges, such as inter-user variation in EMG signals and the influence of noise that may compromise accuracy. Therefore, more diverse data collection and more sophisticated signal processing techniques in the future could further improve the system's performance. Furthermore, while the system has demonstrated good performance in laboratory testing, more extensive field testing in more dynamic environments is needed to ensure the long-term reliability and stability of this adaptive prosthetic system.

Overall, the proposed deep learning approach makes a significant contribution to the development of more responsive adaptive prostheses, with high accuracy and fast response times, which have the potential to improve the quality of life of future prosthesis users.

CONCLUSION

This research has successfully developed and tested a hand gesture recognition system based on EMG signals using an interpretable deep learning model. Experimental results show that the proposed Convolutional Neural Network (CNN) model can classify hand gestures such as gripping, grasping, and waving with an accuracy of up to 95%, which is much better than classical methods such as Support Vector Machine (SVM) and K-Nearest Neighbors (KNN). The advantages of the CNN model lie in its ability to handle the complexity and variability of EMG data, as well as its ability to generalize well to diverse test data.

In addition to accuracy, the system also integrates interpretability techniques using saliency maps, which allow for a better understanding of the parts of the EMG signal used by the model to make classification decisions. This technique provides important insights for researchers and users, and increases system transparency, which is crucial in medical applications such as adaptive prostheses. Using saliency maps, we were able to demonstrate that the model pays more attention to activity in the muscles relevant to each hand movement, increasing trust in the system.

Furthermore, the proposed deep learning model also exhibits excellent inference time performance, with a latency of approximately 15 ms per signal input, making it suitable for prosthesis control applications requiring real-time response. With its fast inference time and high accuracy, this system can be used for adaptive prosthesis control with smooth and responsive motion transitions to user activity.

Overall, this study demonstrates that EMG-based hand gesture recognition using deep learning can provide an effective and efficient solution for adaptive prostheses. The results demonstrate that this approach can improve the quality of life of prosthesis users, enabling them to perform movements more naturally and intuitively. Future work could focus on collecting more diverse data and further developing the system to improve performance in real-world environments. Thus, this approach holds great

potential for prosthesis applications and further development in biomedical-based human-computer interaction.

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