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MG Signals Using Combined Features and Soft Computing Techniques

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Abstract:
Electromyography (EMG) is a widely used technique for analyzing muscle activity and has significant applications in prosthetics, rehabilitation, and neuromuscular disorder diagnosis. The classification of EMG signals remains a challenging task due to their complex, non-stationary nature and susceptibility to noise. To improve classification accuracy, this study employs a hybrid approach that integrates multiple feature extraction techniques with soft computing methods. The proposed methodology involves data acquisition from multiple subjects performing different hand and forearm movements. The raw EMG signals are preprocessed using noise filtering, segmentation, and normalization techniques to ensure high-quality input data. A comprehensive feature extraction process is then applied, combining time-domain features such as Mean Absolute Value, Root Mean Square, Waveform Length, and Zero Crossing, along with frequency-domain features including Mean Frequency, Median Frequency, Power Spectral Density, and Wavelet Coefficients. This combined feature set provides a more detailed representation of the EMG signals, capturing both temporal and spectral characteristics essential for effective classification. The study highlights the importance of integrating diverse feature extraction techniques to enhance EMG signal interpretation. The findings contribute to the development of more accurate EMG-based control systems for assistive technologies, including prosthetic devices and rehabilitation tools. By leveraging a comprehensive approach to EMG signal processing, this research aims to improve muscle activity classification and enable more precise control of biomedical applications. Soft computing techniques, including ANN, SVM Systems, have shown great potential in handling the inherent variability of EMG signals. These methods leverage learning-based approaches to model complex patterns and improve classification accuracy. By integrating time-domain and frequency-domain features, a more comprehensive representation of the EMG signal can be achieved, enabling soft computing models to perform better in distinguishing different muscle activities. Future research will focus on optimizing deep learning techniques for real-time EMG classification and extending the approach to broader applications such as brain-computer interfaces and human-computer interaction. The proposed methodology offers a promising step toward the development of intelligent, high-performance EMG-based systems.

Keywords: Electromyography, EMG Signal Classification, Feature Extraction, Soft Computing, Artificial Neural Networks, Support Vector Machines.

Introduction

Electromyography (EMG) is a widely used technique for recording and analyzing the electrical activity of muscles. It plays a crucial role in various biomedical applications, including prosthetic control, neuromuscular disorder diagnosis, rehabilitation, and human-computer interaction. EMG signals are generated by the activation of motor units within muscles, and their classification is essential for translating muscle activity into meaningful control commands for assistive technologies. However, due to the complex, non-stationary, and noise-sensitive nature of EMG signals, achieving high classification accuracy remains a significant challenge.

Traditional EMG signal classification approaches rely on handcrafted feature extraction and conventional machine learning methods. These techniques include time-domain and frequency-domain feature analysis, followed by classification using algorithms such as k-Nearest Neighbors (k-NN), Support Vector Machines (SVM), and Artificial Neural Networks (ANN). However, single-feature-based classification often fails to capture the full variability of EMG signals, leading to reduced accuracy. To address this limitation, the combination of multiple feature extraction techniques has emerged as a promising strategy to enhance classification performance.

Research Objectives

The primary objective of this study is to improve the classification accuracy of EMG signals by utilizing a hybrid approach that combines diverse feature extraction methods with soft computing techniques. The specific goals include:

1. **Data Collection and Preprocessing** – Acquiring EMG signals from multiple subjects performing different muscle movements and applying noise filtering, segmentation, and normalization.
2. **Feature Extraction** – Extracting time-domain (e.g., Mean Absolute Value, Root Mean Square, Waveform Length) and frequency-domain features (e.g., Mean Frequency, Wavelet Coefficients) to form a robust feature set.
3. **Classification Using Soft Computing Techniques** – Evaluating the performance of ANN, SVM, and Fuzzy Logic classifiers using the combined feature set.
4. **Performance Evaluation** – Comparing classification accuracy, precision, recall, and F1-score of different models to determine the most effective approach.

Literature Review

EMG signals have been studied to diagnose diseases such as muscular dystrophy and neuropathy. Neuromuscular disorders are a group of problems involving the motor nuclei of the brain, spinal cord cells, nerves, and spinal cord that cause muscle weakness. Neuropathy describes damage to the peripheral nerves that carry messages from the brain and spinal cord to the rest of the body. People with muscle diseases may experience temporary fatigue, tingling, tingling, allergic reactions, or muscle weakness, and some symptoms include burning sensation, muscle pain paralysis, or dysfunction in the limbs. Early diagnosis of muscle pain can cure these diseases, so EMG signal analysis has been performed to detect early diseases.

Machine learning methods are widely used in disease diagnosis due to their effectiveness in identifying features [6-8]. In this study, muscle paralysis was estimated because adults and children are affected by strokes [9]. However, spinal cord injury (SCI) and other medical

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conditions can cause muscle weakness, and it is important to determine how SCI affects the body's function, energy, and performance [10]. As information expands, the classification of muscle paralysis becomes stronger and various methods are proposed, with the origin of the difference, body composition and ethology being important. A group of experts on muscle paralysis proposed a revision and a new classification of musculoskeletal diseases [11]. EMG data demonstrate the long-term effects of EMG dysfunction, antagonistic muscles and joints, and muscle dysfunction hypertonicity [12].

Many researchers have developed predictive models based on metrics that measure model performance and learning potential. These measurements include the kinematic coupling that describes the movement of the lower extremities and the electromyographic activity related to the resulting kinematics [13, 14]. Muscle index is calculated by measuring the average electromyographic value of each type of activity [15]. Electromyography shows the results of daily activities, especially knee exercises. Many artifacts affect the EMG signal and time series data are not suitable for demonstration. Traditional techniques use frequency- and time-dependent features to describe EMG features under various knee models [16, 17].

Kamali et al. [23] classified normal, neurogenic, or myopathic muscles by creating a translucent EMG muscle monitor. Predictions were made based on motor potentials (MUPs) using classification based on multiple subjects (MIL). The main aim of this study is to develop a challenge-based MIL to improve the use of EMG techniques. The performance of fuzzy-based MIL, including accuracy, sensitivity, and specificity, was analyzed using current SVM and random forest using different muscle parameters, including proximity and center of arm and leg muscles. Fuzzy models are generally divided into three groups: Takagi-Sugeno-Kang (TSK) model, Mamdani-Larsen model and general fuzzy model; however, only TSK was taken into account since less time was required for defuzzification. In order to achieve good results in signal distribution, the performance of the product needs to be improved.

Gregory and Ren [26] developed a multi-class classifier that uses surface EMG signals to predict the user's continuous motion. The data collection method is based on gait testing and uses various FS methods to estimate the patient's movement along the frontal and sagittal planes. Although FS technology was used in this study, the results showed that the different classes achieved a prediction accuracy of only 77.2%. The established method has difficulty identifying multiple ankle sprains within the limitations of electromyography data. Zhang et al. [27] recorded electromyography signals from 14 patients through three types of knee joint movements, such as walking and sitting. To determine the type of exercise, this study used a class called SVM, in which EMG signals are decomposed by variable value (SVD)-based wavelet transform. EMG features in time and frequency are used to improve the performance of SVM. Accurate verification is achieved by performing five-fold verification for up to fifty iterations. However, this study obtained a poor prediction by using all eigenvectors with wavelet components, which proves once again that FS technology is necessary for good performance. State-of-the-art study clearly shows that the best is required to achieve muscle paralysis performance using proper FS.

Therefore, in this study, the Relief-F FS algorithm is used together with CNN to obtain a good solution, which will be explained in the next section.

Literature Survey

Researcher	Classifier Used	accuracy	Description
Putnam et. al. (1993)	Artificial Neural Network (ANN)	95% accuracy in classification was achieved	AR model parameters-based feature vector for Neural Network • More robust classifier required for persons with disabilities
Jong-Sung Kim et. al. (2004)	Fuzzy Mean Max Neural Network (FMMNN)	Pattern recognition rate of each wrist motions is above 90%, whereas average recognition rate yield 97%	• Six distinctive wrist motions can be classified well • Difference Absolute Mean Value (DAMV) extracted from the EMG signals is used as the input vectors in learning and classifying the patterns
Naik et. al. (2007, 2008), Eman M. ElDaydamony et. al. (2008)	Backpropagation Neural Network (BPNN)	Temporal decorrelation source separation (TDSEP) algorithm-based ICA gives 97% separation efficiency	• RMS value of each signal used to form feature vector as input to neural network • Number of hand gesture identification was restricted to three and six
Alsayegh, Xiang Chen et. al (2007), Jonghwa Kim et al. (2008)	Bayes Network	Average classification rate reported was over 94%	• K-Nearest Neighbour (k-NN) classifier added with Bayes to obtain good result • Addition of accelerator meter with EMG sensors cany increase the classification rate 5-10% • Feature selection is important for better classification and increasing number of features does not always produce good result

Research Gap

The decision-making process of many AI-based predictive models cannot be easily interpreted by practitioners. This lack of explanation can create problems in gaining doctors' trust and incorporating AI-based predictions into healthcare. Although artificial intelligence models can obtain accurate predictions, their clinical validity and effectiveness still need to be determined. Doctors need models that not only make accurate predictions but also provide recommendations that can inform clinical decisions and improve patient outcomes. Future research may focus on collecting and analyzing longitudinal EMG data from individuals at different stages of stroke. Researchers can learn how EMG patterns change over time, which patterns are indicative of particular stages, and how these patterns influence clinical outcomes and clinical response. Advanced machine learning techniques such as recurrent neural networks (RNN) or supervised techniques can be explored to model physical dependency in EMG data.

System Experimentation

Training

In this project study, Artificial Neural Networks were used for classification purposes. A neural network is a computational structure consisting of many layers of interconnected circuits, similar to structures in the brain. Neural networks learn from data, so they recognize patterns, classify data, and are trained to predict future events. Neural networks break down your ideas into layers of abstraction. It can train many samples, such as the human brain, to recognize patterns in speech or images. Character is characterized by the relationship between its elements and the strength or weight of these connections. In this study, a two-layer feedforward network with hidden sigmoid and softmax output neurons (patternnet) was used, which can perform arbitrary operations on vectors as long as there are a sufficient number of neurons in the hidden layer. This network was examined by evaluating the inverse connectivity of gradients (trainscg). Parameters and settings can be adjusted manually. In the feedforward neural network, the extracted features are given as input, and the output is given as a binary number according to the category. The number of displayed processes is the same as the number of groups, while the hidden process depends on the user's choice. We extracted 11 features from each sample (160 samples in total). An 11x160 array is taken as input. The duration of the transaction is 1000. There are two (number of groups) output layer and output layer. Now our series is ready for training. Lines 77 to 84 are shown to illustrate this idea. Column 77 is the feature extracted from signal 77. model with output 10 (sick). For column 84, the signal with output 0 1 (good) contains the features extracted from model 84. After the data is in and out of the system, we need to train it. To do this, the neural network needs three sets of data: training, validation, and testing. We need to set a percentage for analysis and evaluation of events. 30% is used (15% validation and 15% testing) and the remaining 70% is used for training. This is how MATLAB trains artificial neural networks. The network itself uses 15% of the test data to demonstrate the accuracy of the network.

Testing

After training the network, we need to test the accuracy of the network. To do this, we create an array of 11x100. There are 100 samples in the series (50 patients, 50 healthy) [5]. 11 is the number of cluster-like features extracted from training. The number and type of tests are shown in Table 1.

Subjects	Muscle type	No. of subjects	No. of samples
Healthy	Biceps brachii	5	09
Patient	Biceps brachii	6	15

Table 1. Samples taken from different subject groups for testing

Results and Discussion

With the help of MATLAB, we created a neural network that can distinguish between sick and healthy states. In short, we can understand whether a person has a neuromuscular disease or not and whether he or she uses the internet. After training the sequence we created, the network provided the confusion matrix. This confusion matrix gives us the truth of the network. The overall accuracy of our network is 85%. Training the network in MATLAB is divided into 3 parts: training, validation and testing (the real network uses this to check the performance of the network after training). Here, 80 samples were taken from each group. tested (11 were found to be healthy). The overall accuracy of classifying sick and healthy patients was 85%. After training our network, we need to create another series to test it. In our test series, 50 samples were taken from patients and 50 samples from healthy subjects. The size of the array is 11x100, where 11 is a number. Features (the same features used for training). 39 of 50 samples were classified into the patient group with 78% accuracy, while 37 of 50 samples were classified into the patient group with 74% accuracy. So the real average for healthy people and patients is 76%. Our test is 76% accurate and the website test is 75% accurate. The error is 1.32%, so we can say that the accuracy increased by 1.32% when we tested the model in which the sequence was created. However, if we compare the results with an overall accuracy of 85%, the error is 10.6%.

Conclusion

An artificial neural network architecture has been successfully applied for the recognition of myoelectric signals. Neural networks are useful tools to separate EMG signals into two different groups, such as health signals and patient problems. Electromyographic signals produced by human muscles are often used for medical diagnosis. Based on our testing results, we found that the truth was not used to complete the process. The aim of this study is to propose an EMG classification. Negativities or problems in the system may lead to the development of other methods. In this study, EMG signal analysis techniques that can be used in all biomedical research, diagnosis, end-use and hardware applications are introduced. The accuracy of the classification is good. Classification performance of course, based on the type of features derived from the EMG recordings

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