

CLASSIFICATION OF EMG SIGNALS USING ARTIFICIAL INTELLIGENCE

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Abstract: *This article discusses the classification of electromyography signals using artificial intelligence methods. Electromyography signals reflect the electrical activity of muscles and are widely used in biomedical engineering, rehabilitation, prosthetic control, human-computer interaction, and clinical diagnostics. The classification of EMG signals is a complex task because these signals are nonlinear, noisy, and highly dependent on individual physiological characteristics. Artificial intelligence methods, including machine learning and deep learning, provide effective tools for extracting features, recognizing muscle activity patterns, and improving classification accuracy. The article analyzes the main stages of EMG signal processing, feature extraction, AI-based classification methods, applications, challenges, and future prospects.*

Keywords: *artificial intelligence, EMG signals, electromyography, signal classification, machine learning, deep learning, biomedical engineering, feature extraction, prosthetic control.*

INTRODUCTION

Electromyography is a biomedical technique used to record the electrical activity produced by skeletal muscles. EMG signals are generated when muscle fibers are activated by the nervous system. These signals contain important information about muscle contraction, movement intention, fatigue, and neuromuscular function. For this reason, EMG analysis is widely used in medicine, sports science, rehabilitation, and biomedical engineering.

One of the most important tasks in EMG signal analysis is classification. EMG classification means identifying different muscle activities, gestures, movement types, or pathological conditions based on recorded signals. For example, EMG signals can be used to classify hand gestures for prosthetic control, detect muscle fatigue in athletes, or support the diagnosis of neuromuscular disorders.

However, EMG signals are difficult to analyze because they are affected by noise, electrode placement, skin condition, muscle fatigue, movement artifacts, and individual differences between users. Traditional signal processing methods are useful, but they may not always provide high accuracy in complex classification tasks. Artificial intelligence offers





powerful methods for learning patterns from EMG data and improving classification performance.

Nature of EMG Signals

EMG signals can be recorded using surface electrodes placed on the skin or invasive needle electrodes inserted into the muscle. Surface EMG is more common in engineering and rehabilitation applications because it is non-invasive and easier to use. However, surface EMG signals are often affected by external noise and interference from neighboring muscles.

EMG signals usually have low amplitude and complex frequency characteristics. Before classification, they must be processed carefully. The main steps include signal acquisition, filtering, segmentation, feature extraction, classification, and evaluation. Each stage affects the final accuracy of the system.

Filtering is necessary to remove noise and unwanted components. For example, power line interference, motion artifacts, and high-frequency noise can distort the signal. After filtering, the signal is divided into time windows or segments. These segments are then used to extract meaningful features.

Feature Extraction from EMG Signals

Feature extraction is one of the most important stages in EMG classification. Features are numerical characteristics that describe the signal and help the classifier distinguish between different classes. Good features improve accuracy and reduce computational complexity.

Time-domain features are widely used because they are simple and effective. These include mean absolute value, root mean square, waveform length, zero crossing, slope sign change, and variance. Such features describe signal amplitude, energy, and complexity.

Frequency-domain features are also useful. They include mean frequency, median frequency, power spectrum, and frequency distribution. These features are often used to analyze muscle fatigue and changes in muscle activity.


Time-frequency methods, such as wavelet transform, provide information about both time and frequency characteristics. They are useful because EMG signals are non-stationary, meaning their properties change over time.

In recent years, deep learning methods have reduced the need for manual feature extraction. Neural networks can learn features automatically from raw or minimally processed EMG signals. However, deep learning usually requires larger datasets and more computational resources.

Artificial Intelligence Methods for EMG Classification

Machine learning methods have been widely used for EMG signal classification. Common algorithms include support vector machines, k-nearest neighbors, decision trees,





random forests, artificial neural networks, and linear discriminant analysis. These methods can classify different muscle movements based on extracted features.

Support vector machines are popular because they perform well in high-dimensional feature spaces. They are often used for hand gesture recognition and prosthetic control. Random forests are useful because they combine many decision trees and can handle complex feature relationships. K-nearest neighbors is simple and effective but may be slower with large datasets.

Artificial neural networks can model nonlinear relationships in EMG data. They are suitable for recognizing complex movement patterns. Deep learning methods, especially convolutional neural networks and recurrent neural networks, have shown strong potential in EMG classification. Convolutional neural networks can extract local patterns from EMG segments, while recurrent neural networks and long short-term memory networks can model temporal dependencies.

Hybrid approaches are also used. For example, wavelet transform may be combined with neural networks, or handcrafted features may be classified using support vector machines. The choice of method depends on dataset size, application type, computational requirements, and desired accuracy.

Applications of AI-Based EMG Classification

One of the most important applications of EMG classification is prosthetic control. Artificial intelligence can classify muscle signals related to different hand or arm movements. This allows a prosthetic device to respond to the user's movement intention. For example, EMG signals can be used to distinguish between grasping, opening the hand, wrist rotation, or finger movement.

EMG classification is also used in rehabilitation. Patients recovering from stroke, injury, or neuromuscular disorders can use EMG-based systems to monitor muscle activation and receive feedback during therapy. AI can help evaluate progress and personalize rehabilitation exercises.


Another application is human-computer interaction. EMG signals can be used as control commands for computers, robots, wheelchairs, or virtual environments. This is especially useful for people with limited mobility.

In sports science, EMG analysis helps study muscle fatigue, training effectiveness, movement technique, and injury risk. AI-based classification can help identify patterns of muscle overload or inefficient movement.

Clinical diagnostics is another important field. EMG signals can support the detection of neuromuscular disorders, although clinical diagnosis must always be performed by medical professionals using comprehensive evaluation.

Challenges in EMG Classification





Despite its potential, EMG classification faces several challenges. First, EMG signals vary significantly between individuals. A model trained on one person may not work equally well for another. Therefore, personalization and adaptive learning are important.

Second, electrode placement affects signal quality. Even small changes in electrode position may change the recorded signal. This can reduce classification accuracy in real-life use.

Third, muscle fatigue changes EMG signal characteristics over time. A classifier trained at the beginning of a session may become less accurate later. Adaptive models are needed to handle such changes.

Fourth, datasets are often limited. Deep learning methods require large and diverse datasets, but collecting EMG data can be time-consuming. Data augmentation and transfer learning may help solve this issue.

Fifth, real-time classification requires fast and efficient algorithms. In prosthetic control or human-machine interfaces, delays must be minimal. Therefore, models must be accurate and computationally efficient at the same time.

Future Prospects

The future of AI-based EMG classification is connected with more adaptive, personalized, and real-time systems. Transfer learning may allow models trained on large datasets to be adapted quickly to new users. Deep learning architectures may improve automatic feature learning and reduce manual preprocessing.

Another promising direction is multimodal signal analysis. EMG can be combined with accelerometer data, inertial sensors, electroencephalography, or computer vision to improve classification accuracy. Such systems may be more robust in real-life conditions.

Wearable technology will also play an important role. Compact EMG sensors integrated into armbands, rehabilitation devices, or smart clothing can make EMG-based applications more accessible.


In medical and rehabilitation fields, AI can help create personalized therapy systems that adjust exercises according to muscle activity and patient progress. In prosthetics, improved EMG classification may lead to more natural and intuitive control.

Conclusion

In conclusion, artificial intelligence provides effective tools for classifying EMG signals. Machine learning and deep learning methods can recognize muscle activity patterns, support prosthetic control, improve rehabilitation systems, and contribute to biomedical research.

However, successful EMG classification requires careful signal acquisition, preprocessing, feature extraction, model selection, and evaluation. Challenges such as noise, individual variability, electrode placement, muscle fatigue, and limited datasets must be addressed.





AI-based EMG classification is a promising direction in biomedical engineering. With further development of adaptive algorithms, wearable sensors, and personalized models, EMG-based systems may become more accurate, practical, and widely used in healthcare and human-machine interaction.

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