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# Optimization and Application of Gesture Classification Algorithm Based on EMG

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**Abstract:** Electromyographic signals (EMG) have a wide range of applications in biomedicine, intelligent human-computer interaction, and rehabilitation assistance. However, due to noise interference, individual differences, computational complexity, and other issues, traditional classification strategies still face challenges in terms of accuracy, stability, and real-time performance. In this paper, the traditional EMG gesture classification methods are comprehensively investigated, and data enhancement, feature mining and lightweight deep learning models are used to improve their accuracy and real-time performance. Moreover, multiple modes are combined to optimize boundary processing to improve real-time performance and robustness. Based on various published databases and practical application environments, the proposed optimization algorithm has demonstrated significant improvements across multiple evaluation metrics, showing both high feasibility and practicality. Meanwhile, the possibility of applying the algorithm to intelligent prosthetics, intelligent human-computer interaction, rehabilitation assistance and other fields is discussed, so as to promote the progress of EMG gesture recognition technology.

**Keywords:** electromyography signal; gesture recognition; deep learning

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## 1. Introduction

With the development of artificial intelligence and biomedicine, gesture classification algorithm based on electromyography (EMG) has become an important research direction of human-computer interaction, rehabilitation training and wearable devices. EMG signals can reflect the activity information of muscles and transmit the user's instructions to prosthetic devices, robot operations and intelligent devices. However, due to the large noise interference, physical differences of users and difficulties in feature extraction, the traditional EMG gesture classification method has some characteristics such as poor anti-interference ability and poor real-time performance. Therefore, to optimize the gesture classification algorithm of EMG signals and enhance the adaptability, response speed and operation efficiency of the system is a hot research topic. This paper mainly studies the gesture classification algorithm based on EMG signal, seeks data-driven directions such as EMG signal enhancement, lightweight deep learning structure establishment and efficient classification decision methods, and verifies them in practical application environments to optimize the performance of EMG-based gesture recognition.

## 2. Basic Concept of EMG Gesture Classification

### 2.1. Basic Principle of Electromyography (EMG)

EMG is the electrical activity signal caused by muscle contraction, which is the bioelectrical signal generated by the action of motor neurons on muscle fibers. There are two kinds of EMG: surface electromyography (sEMG) and deep electromyography (iEMG) [1]. The former is non-invasive, but easy to be disturbed by environmental noise. The latter obtains the EMG signal through the deep needle electrode, the EMG signal quality is high, but the operation is complicated. The main characteristics of EMG are amplitude, frequency and time information, and the intensity of EMG is usually 0 ~ 10mV, and the spectrum range is basically 10 ~ 500Hz. In general, the EMG signal can be modeled as the following formula:

$$EMG(t) = \sum_{i=1}^{N} M_i(t) \cdot A_i \cdot e^{j\theta_i} \tag{1}$$

Where $M_i(t)$ represents the action potential of a single muscle fiber, $A_i$ represents the amplitude, $e^{j\theta}$ represents the phase shift, and N represents the number of muscle fibers. Due to physiological factors (such as skin resistance, fatigue) or external factors (such as electrode noise, active artifacts, etc.), the quality of EMG signal often changes, so it is usually necessary to preprocess it, mainly including filtering (low-pass, high-pass, band-pass), data normalization, signal amplification, etc. For EMG signals, their properties can be time domain characteristics (RMS value, ZC ratio), or frequency domain characteristics (STFT, WT), or a combination of both (STFT, WT). In order to obtain a higher classification accuracy, it is necessary to select a good feature extraction method and optimize it.

### *2.2. Basic Method of Gesture Classification*

Gesture classification methods are mainly based on EMG, and there are two main methods: traditional machine learning and deep learning. Traditional machine learning methods use artificial feature extraction, and common classifiers include support vector machine (SVM), random forest (RF) and K-nearest neighbor (KNN). For example, SVM divides gesture categories by constructing a hyperplane, and its optimization objective function is as follows:

$$\min_{w,b} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\xi_i \tag{2}$$

Where $W$ is the weight vector, $b$ is the bias, is the relaxation variable, and $C$ is the regularization parameter. Although traditional methods are easy to operate, their classification performance mainly depends on feature extraction, making it difficult to adapt to the complexity of EMG signals.

Deep learning models avoid manual feature design and automatically extract features. Convolutional neural networks (CNNs), long short-term memory networks (LSTMs), and Transformers are the most widely used deep learning models. CNN extracts local features through convolution operation, and its mathematical expression is as follows:

$$F_{out} = Re\,L\,U(W * F_{in} + b) \tag{3}$$

Where $W$ is the convolution kernel, * represents the convolution operation, $F_{in}$ and $F_{out}$ are the input and output feature maps respectively, and b is the offset term. The advantage of Transformer is that it can improve the classification accuracy by using its own attention mechanism, and the combination of LSTM's processing of time information is complementary to each other. The gesture recognition process involves data acquisition, pre-processing, feature extraction, model building, and classification. And we are mainly committed to improving classification performance while considering real-time constraints, in order to enhance applications in intelligent prosthetics, human-computer interaction, and other areas.

## 3. Optimization of EMG Gesture Classification Algorithm

### *3.1. Data-Driven Signal Enhancement and Feature Optimization*

Due to electrode noise, motion artifacts, and industrial frequency interference (50/60Hz), poor-quality EMG signals can compromise recognition accuracy; thus, signal enhancement and feature extraction are necessary. Signal pre-processing is an essential step before classification, involving the use of a band-pass filter (10-500 Hz), wavelet denoising, and wavelet transform to remove noise and retain effective signals. The core of

EMG gesture classification lies in feature extraction technology. It includes time domain characteristics (RMS, zero-crossing, ZC, etc.), frequency domain characteristics (power-spectral density, PSD, etc.) and time-frequency domain characteristics (STFT, wavelet transform). The robustness of the model can be improved by applying data augmentation techniques, such as signal transformation and synthetic data generation, to make EMG recognition more stable.

Figure 1 shows the complete processing flow of EMG signal. From data acquisition, signal filtering (bandpass/wavelet), feature extraction (RMS/ZC/PSD), time-frequency analysis (STFT/WT) to data enhancement (GAN/data amplification) and classification model training, the optimized signal features can effectively improve the accuracy and robustness of gesture classification.

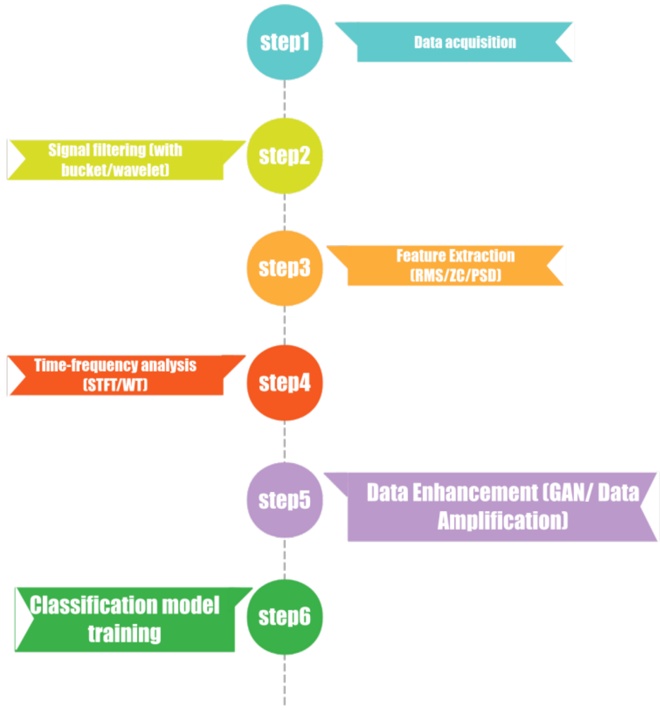


**Figure 1.** Flow Diagram of EMG Signal Enhancement and Feature Extraction.

*3.2. Lightweight Deep Learning and Adaptive Modeling*

Traditional EMG gesture classification models based on deep learning have strong computational burden and are not suitable for terminal devices with limited resources [2]. To this end, scholars have proposed lightweight deep learning models and adaptive modeling to reduce the computational burden and improve the adaptability of the models. Lightweight neural networks are more structured and efficient networks that use model pruning, quantization and knowledge distillation. For example, MobileNet uses deep separable convolution to reduce computational complexity while maintaining high classification accuracy. The convolution formula is as follows:

$$F_{out} = Re\,L\,U(W_d * (W_p * F_{in}) + b) \tag{4}$$

Where, $W_d$ is the deep convolution kernel, $W_p$ is the point-by-point convolution kernel, $F_{in}$ and $F_{out}$ is the input and output feature maps respectively, and $b$ is the offset term.

Adaptive modeling based on transfer learning and online learning can make the model have EMG data suitable for different users, so as to reduce the modeling cycle and improve the accuracy of classification. For example, the transfer learning objective function is:

$$\theta^* = arg \min_{\theta} \sum_{i=1}^{N} L(f_\theta(x_i), \ y_i) \quad (5)$$

Where $\theta$ is the model parameter, $L$ is the loss function, $x_i$ and $y_i$ respectively are the input data and labels.

### 3.3. Intelligent Classification Decision and Real-Time Computing Acceleration

The key problem of EMG gesture classification is to optimize the gesture classifier and speed up the calculation, so as to better meet the real-time and improve the application value [3]. Although traditional machine learning algorithms (such as SVM, RF and KNN) have high computational speed, they lack high classification accuracy. Deep learning applications (such as CNN, LSTM, Transformer) can automatically obtain data characteristics, but the computational complexity is higher. Therefore, integration technology, focus strategy and small sample learning are important means to improve quality. In terms of computer computing speed, methods such as model compression (calculated as INT8), pruning, or knowledge transfer can reduce the burden on the computer. In addition, with the guidance of edge computing, reliance on cloud computing is reduced to enable fast EMG recognition.

Figure 2 shows how different computational acceleration methods (model quantization, pruning, knowledge distillation, edge computing) improve the classification speed of EMG. As you can see, edge computing has seen the largest speed increase (25%), followed by model quantification (20%), knowledge distillation (18%), and pruning (15%). The figure clearly shows the optimization effects of different methods, which is helpful to select a computational acceleration strategy suitable for EMG classification and improve the real-time and applicability of the system.

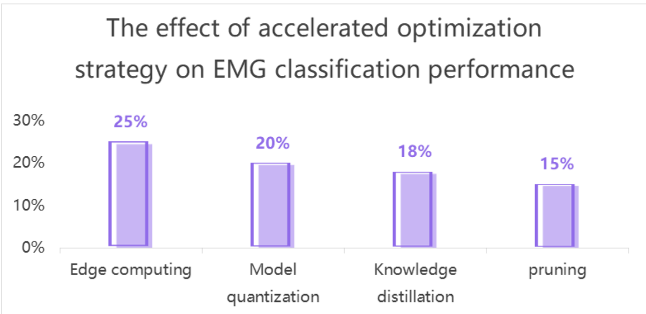


**Figure 2.** Calculating the Effect of Accelerated Optimization Strategy on EMG Classification Performance.

## 4. Application of EMG Gesture Classification Algorithm

### 4.1. Human-Computer Interaction and Intelligent Control

With the development of artificial intelligence and human-computer interaction technology, the use of EMG signals to recognize palm movements has played a crucial role in the application of robot manipulation, smart homes, virtual augmented reality (VR/AR). The study of EMG signals can effectively and accurately reflect muscle activity, and at the same time, deep learning algorithms can be used to achieve effective human-machine interaction, improve the user's sense of experience and control accuracy [4]. Gesture recognition is used to control the robot arm, grasp, move and rotate the robot arm, and is widely used in robot control, such as the robot arm, which can be used in the assembly line operation of the factory, when the distance between the robot and the operator is limited, the use of the robot in the dangerous working environment, medical rehabilitation, etc. For example, the user recognizes gestures based on the electrical signals of the user's muscle contractions, thereby accurately positioning the grasp, movement, and rotation of the manipulator. In the smart home management system, based on EMG gesture recognition, lighting, household appliances and audio can be controlled, improving the convenience of users, especially those with poor physical conditions. In the VR/AR interactive system, gesture recognition based on EMG can effectively control games or virtual practice activities, which can provide a more natural user experience. In the future, with the continuous improvement of the accuracy of EMG sensors and the continuous maturity of deep learning, the efficiency of human-computer interaction and intelligent control system will be further improved, and it will be widely used in medical rehabilitation treatment, remote control, intelligent prosthetics and other fields.

Figure 3 shows the application flow of EMG gesture recognition in the fields of robot control, smart home, and VR/AR interaction. The whole process includes EMG signal acquisition, feature extraction (RMS/ZC/PSD), gesture classification modeling, control command generation, and is finally used in a variety of interactive scenarios. This framework helps to understand the application of EMG technology in the field of intelligent control.

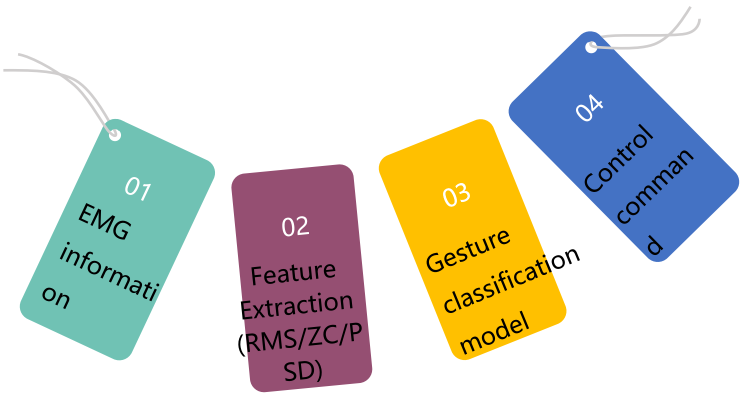


**Figure 3.** Application Framework of EMG Gesture Recognition in Human-Computer Interaction.

*4.2. Medical Treatment and Rehabilitation Assistance*

Gesture recognition technology based on EMG has a wide range of applications, mainly in intelligent prosthesis control, neural rehabilitation training, and sports injury monitoring [5]. Since EMG signals can directly reflect muscle activity, combining machine learning and deep learning algorithms can provide patients with more accurate and effective rehabilitation programs. For patients who have lost limbs, intelligent prosthetics based on EMG gesture recognition can be used to operate, so that they can make natural human grip, turn and stretch. The EMG signal collected at the residual muscle is analyzed by the classification algorithm to determine the gesture type, enabling the intelligent prosthesis to perform gripping, turning, and stretching movements. The control strategy of the intelligent prosthesis can be modeled as follows:

$$\hat{y} = argmax\, P\,(y|X) \tag{6}$$

Where X is the myoelectric feature input, y is the predicted gesture class, and P(y|X) is the output probability distribution of the gesture classification model. The optimized EMG signal classification algorithm can improve the response speed and accuracy of the prosthesis, so that patients can operate the prosthesis more smoothly and improve the quality of life.

For patients with stroke and spinal cord injury, rehabilitation systems based on EMG technology can be used to detect their muscle activity and guide their personalized recovery process. For example, smart rehabilitation gloves can detect muscle activity levels by detecting EMG information and provide strength feedback training to help patients regain fine hand operation. Based on real-time myoelectric status information, patients become more aware of their recovery status, which can help them adjust their training accordingly. EMG signals can also be used to detect muscle fatigue so that trainers can adjust exercise intensity in time to prevent patients from being injured due to overtraining. For example, therapists can use EMG signals to detect muscle activity status in real time during rehabilitation, so as to guide rehabilitation physicians to adjust rehabilitation programs to achieve good results.

Table 1 compares the applications of EMG technology in intelligent prosthetics, neurological rehabilitation, and sports injury monitoring, listing the target groups, core technologies, key advantages, and key challenges. For example, smart prosthetic control is mainly aimed at amputees, using EMG classification and machine learning to improve the accuracy of prosthetic control, but its main challenges are signal stability and computing resource requirements. The table helps to understand the different application scenarios and key technologies of EMG in the medical and rehabilitation fields.

**Table 1.** Comparison of the Application of EMG in Medical Treatment and Rehabilitation Assistance.

| Application field | Target group | Core technology | Major advantage | Major challenge |
|---|---|---|---|---|
| Intelligent prosthesis control | amputee | EMG classification, machine learning | Improve the control accuracy of prosthesis | Signal stability, computing resource requirements |
| Neurorehabilitation training | Stroke/spinal cord injury patients | Real-time electromechanical feedback, training evaluation | Personalized rehabilitation training | Data adaptability, long training cycle |
| Sports injury detection | Athletes/recovering patients | Muscle fatigue detection, signal analysis | Real-time monitoring to prevent overtraining | Individual differences, device portability |

### *4.3. Wearable Devices and Edge Computing*

The application of EMG gesture classification technology in wearable and edge computing devices places great emphasis on real-time processing capabilities, enabling various smart wristbands, smart gloves, and other devices to achieve real-time gesture recognition with low power consumption. On the basis of EMG gesture recognition, deep learning and edge computing can be used to realize efficient and low latency gesture recognition. For example, smart wristbands and smart gloves collect human electromyogram signals through EMG sensors to collect gestures and issue corresponding gesture commands. Smart gloves can assist the hearing-impaired to convert gestures into text or speech. Smart wristbands can be used for fitness training and health care, showing users the real-time movement of human muscles. In the past, gesture EMG recognition systems were cloud-based and could not cope with the demands of instant interaction due to latency. Edge computing can be applied directly to the EMG data processing on the device itself, reducing transfer time and increasing response speed. Additionally, lightweight deep learning architectures (such as MobileNet) can be deployed on wearable devices to achieve energy-efficient and cost-effective gesture classification. The Internet of Things (IoT) technology for EMG gesture recognition can also leverage the architecture of multiple devices in parallel with the cloud and surrounding devices, such as home automation management or medical testing. Users can use EMG gestures to control lamps or electric appliances in their homes, thus increasing user convenience. In medical applications, EMG portable devices can also continuously measure the patient's muscle movement and transmit this physiological data to the cloud through the network for remote analysis by physicians.

Figure 4 shows the research distribution of EMG in different application areas such as smart wristbands, smart gloves, low-power computing, and IoT medical monitoring. It can be seen that smart wristbands and smart gloves account for the highest proportion, indicating that these devices are widely researched and applied in the field of EMG. Low-power computing and IoT medical monitoring are also gradually developing to improve the real-time and remote monitoring capabilities of the system. These trends indicate that EMG gesture recognition has a promising future in wearable devices and edge computing.

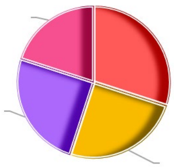


**Figure 4.** Application Proportion of Wearable Devices and Edge Computing in EMG Gesture Recognition.

## 5. Conclusion

This paper focuses on the processing and practical methods of gesture classification based on EMG, including signal pre-enhancement, feature processing, lightweight deep neural network processing, and fast processing speed, so as to further optimize the classification performance and improve the real-time performance. The application scenarios of EMG gesture recognition, including human-computer interaction, rehabilitation treatment, smart wearable devices and other fields are introduced in depth. Although EMG gesture recognition has made great progress at present, signal noise, individual differences, and compatibility of different devices are still factors restricting further development. In the future, the stability and applicability of the system can be improved from the aspects of multi-information fusion, transfer learning, cloud and edge collaborative computing. With progress in artificial intelligence and perception, EMG gesture recognition will play a greater role in intelligent interaction, medical assistance, wearable computing, and other areas, providing human-machine communication with more accurate, efficient, and convenient methods.

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