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Review

Optimization of Neural Motor Control Model Based on EMG Signals

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Abstract: As an important signal of the nervous system, electromyography (EMG) is used in prosthesis control, rehabilitation training, motion intention prediction and human-computer interaction. However, its widespread application is limited by noise, large individual differences, complex computation and poor real-time performance. In this paper, the processing technology, feature extraction, control mode design and calculation optimization based on EMG are reviewed, and optimization strategies based on signal enhancement, deep modeling and accelerated calculation are proposed to ensure the robustness and timeliness of the algorithm and improve the adaptability of motion control to individuals. The results show that the optimized model can effectively improve the precision of motion control, calculation speed and cross-individual compatibility, and provide technical support for EMG intelligent prosthetics, rehabilitation AIDS and wearable neural interfaces.

Keywords: EMG signal; neuromotor control; optimization algorithm

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1. Introduction

Electromyography (EMG) is the main driving device of the body movement through the joint participation of the nervous system and muscles in the movement plan, which is used in the control of intelligent prosthetics, training in rehabilitation sports, monitoring in sports competitions and interaction with machines. In traditional EMG exercise mode, due to the influence of signal noise interference, individual differences, muscle fatigue and other factors, EMG exercise management does not have high accuracy, universality, real-time and other problems, resulting in its low application. In recent years, research and development based on deep learning, signal enhancement, and energy-saving computing have provided more possibilities for further improvement of EMG controller models. This paper mainly focuses on EMG analysis, feature extraction, motion control modeling and algorithm acceleration, and uses signal optimization, neural network establishment, real-time computing acceleration and other methods to improve the stability, efficiency and cross-user adaptability of the model, so that the model can play a greater value in intelligent prosthetics, rehabilitation assistance and wearable neural interfaces.

2. Basic Concepts of EMG Signal and Neural Motor Control

2.1. Physiological Basis of EMG Signal

EMG is the bioelectrical signal of muscle movement, which reflects the electrical stimulation of nerve to muscle fibers. According to the different collection methods, it can be divided into two categories: epidermal electromyography (sEMG) and deep electromyography (iEMG). The former is recorded with skin electrodes and is suitable for non-invasive monitoring, such as bionic hand movement, rehabilitation, human-computer interaction, etc [1]. The latter is recorded with needle-like electrodes, and the signal quality is good, but it is invasive, and it is mainly used in medical diagnosis, fine movement and other fields. The typical features of EMG signal include time domain feature (RMS, mean absolute value (MAV)), frequency domain feature (power spectral density (PSD), median, short time Fourier transform (STFT), wavelet transform). The different types of EMG signals and their characteristics are as follows in Table 1.

Table 1. Classification and characteristics of EMG signals.

EMG type	Acquisition mode	advantage	shortcoming	Application field
Surface electromyography (sEMG)	Skin surface electrode	Non-invasive, suitable for large muscle groups	Susceptible to skin impedance and electrode position	Prosthetic control, rehabilitation training, human-computer interaction
Deep myoelectricity (iEMG)	Needle electrodes are inserted into the muscle	High signal-to-noise ratio for deep muscles	It is highly invasive, and the collection process is uncomfortable	Medical diagnosis, fine motor analysis

Table 1 compares the collection methods, advantages and disadvantages and application fields of surface electromyography (sEMG) and deep electromyography (iEMG). sEMG uses skin electrode acquisition, which is suitable for prosthesis control, rehabilitation training and human-computer interaction, but is easily affected by skin impedance. iEMG is inserted into the muscle through needle electrodes, the signal quality is high, but invasive, and it is mainly used in medical diagnosis and fine motor analysis. This table helps to understand the characteristics of EMG signals and their applicability in different scenarios.

2.2. Theoretical Framework of Neural Motor Control Model

The neural motor control model describes the motor coordination behavior between the brain, spinal cord and muscle groups, and EMG is the embodiment of the motor instructions in the muscles of these control mechanisms. There are three main types of behavior control models driven by EMG signals: (1) Pattern recognition model: Machine learning or deep learning methods are used to map EMG signals to specific gestures or motor actions [2]. Common methods include support vector machine (SVM), random forest (RF), convolutional neural network (CNN), etc. (2) Kinematic model: Mathematical model of EMG signal to behavior output based on physiological and physical characteristics of musculoskeletal structure, mainly used for rehabilitation training and biofeedback control. (3) Hybrid model: Combining pattern recognition model and kinematic model, the model is more conducive to accurate and flexible behavior control, and is applied to intelligent prosthetics and human-computer interaction.

Figure 1 shows the role of EMG signals in neural motor control. EMG signals are generated from the brain-spinal-muscle system and input to different neural motor control models (pattern recognition model, muscle dynamics model, mixed control model) through signal acquisition, and finally applied to prosthetic limb control, rehabilitation training and intelligent human-computer interaction. Different modeling methods are suitable for different task scenarios, such as pattern recognition models for prosthetic limb control, dynamics models for rehabilitation training, and hybrid models for more complex intelligent interactive systems.

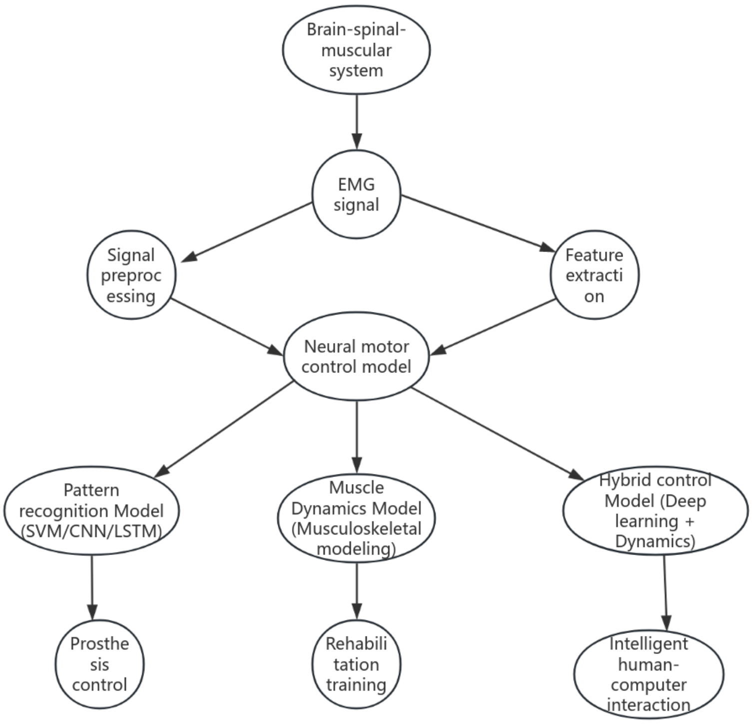

Figure 1. Neural motor control framework driven by EMG signal.

2.3. EMG -Driven Neuromotor Control Applications

Electromyography (EMG) is a direct reflection of muscle activity and is widely used in motion understanding and analysis, intelligent prosthetic control, rehabilitation training and human-machine interaction. By using EMG to control human movement, the control system can obtain the key information from the signal, and then convert it into the actual execution command through a series of processing to achieve natural and accurate control [3]. (1) The use of EMG signals of muscle activity can accurately control the basic activities of multi-joint myoelectric prostheses (such as grasping, rotating and stretching), so that disabled patients can perform the basic functions required for life. Deep learning based pattern classification systems (CNN and LSTM) can effectively identify real-time EMG signals and determine hand posture intent, thereby helping to improve the flexibility and reliability of prosthetics. (2) EMG has important applications in stroke rehabilitation and spinal cord injury repair, which can monitor the muscle activity of patients and provide biofeedback information to assist rehabilitation training. For example, intelligent rehabilitation gloves can be used to train patients' hand rehabilitation based on EMG feedback data to improve muscle activity. (3) EMG can also be applied to human-computer interaction and VR systems to control virtual objects through gestures to make communication more immersive. For example, gloves based on EMG can be applied to remote control of robots, games and other scenes, so that the interaction is more natural and intuitive.

Figure 2 shows the proportion of EMG signals used in different fields. Among them, intelligent prosthesis control (35%) is mainly used for accurate operation of myoelectric prosthesis, neural rehabilitation training (30%) combines with intelligent devices to monitor muscle recovery, human-computer interaction (20%) uses EMG for gesture recognition and remote control, and exercise training (10%) monitors muscle fatigue and movement patterns. Other applications (5%) are in areas such as biofeedback and medical monitoring.

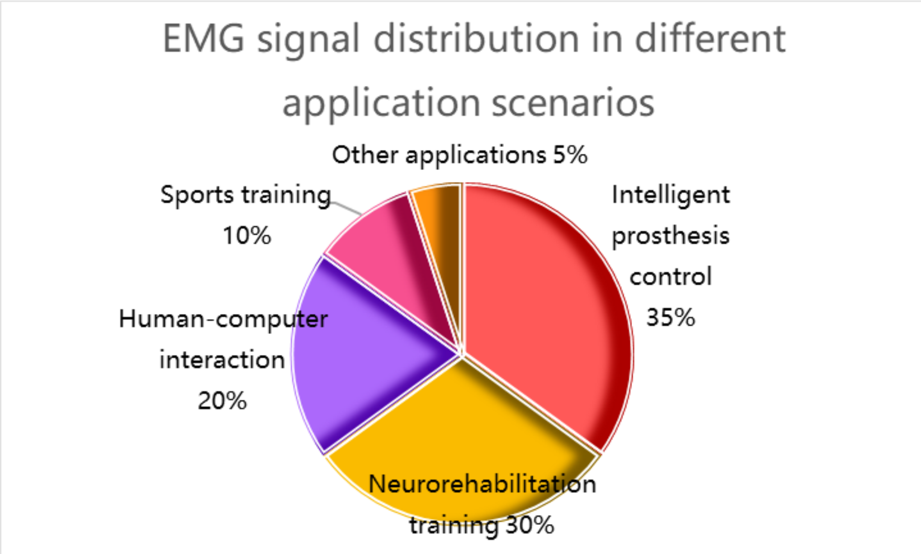

Figure 2. Distribution of EMG signals in different application scenarios.

3. Problems Faced by Neural Motor Control Models

3.1. Core Difficulties of EMG Signal Processing: From Noise Intervention to Individual Adaptation

Due to noise interference, individual differences, muscle fatigue and other factors, the stability and classification accuracy of EMG signals will decline. Noise interference is mainly caused by poor electrode contact, false electromotive force signal, industrial electric field interference (50/60Hz), resulting in a decrease in signal to noise ratio (SNR), which affects the accuracy of gesture recognition. Bandpass filtering, Kalman filtering and wavelet filtering are commonly used, but these filtering technologies can not meet the application requirements in high dynamic environment. Individual specificity is another serious problem in EMG recognition. Due to the different bone and skin structures of each person, their resistance and signal amplitude are different, so the existing universal model can not cover all operators. In addition, muscle fatigue will also cause changes in the amplitude and spectral components of EMG, which will affect the long-term stability of the model. In order to solve the above problems, methods such as adaptive modeling, customized model training and data enhancement (such as generating new data samples through GAN) can be introduced to enhance the generalization ability and adaptability of the model, but it is still necessary to weigh the possible computational cost and reaction efficiency. How to make the system more stable while ensuring its high efficiency is an important problem worth studying.

Table 2 compares the main effects of EMG signals in terms of noise interference, individual differences, and muscle fatigue, and the corresponding solutions. For example, noise interference will reduce the signal-to-noise ratio and affect the classification accuracy. Common solutions include bandpass filtering, wavelet denoising and Kalman filtering. Individual differences affect the adaptability of the model, which can be optimized by adaptive modeling, personalized training and transfer learning. Muscle fatigue affects long-term stability, which is often adjusted by data enhancement (GAN), online learning, and real-time signal compensation.

Table 2. Core challenges and solutions for EMG signal processing.

Problem type	Major influence	Common solutions
Noise interference	Reduce the signal signal-to-noise ratio (SNR) and affect the classification accuracy	Bandpass filtering, wavelet denoising, Kalman filtering

Individual difference	The EMG signal amplitude and characteristics of different users are different, and the model adaptability is poor	Adaptive modeling, personalized training, transfer learning
Muscle fatigue	Muscle fatigue leads to the change of signal frequency, which affects the long-term stability of the model	Data enhancement (GAN), real-time signal compensation, online learning

3.2. Adaptability and Limitations of Traditional Neural Motor Control Models

Traditional neural motor control models mostly rely on machine learning and statistical modeling methods, such as SVM, RF and KNN [4]. However, because feature selection is too sensitive, it is difficult to process the variability of individual EMG signals. In view of the dynamic nature of EMG signals, static feature extraction methods (such as RMS and ZC) are used, but the classification model is not applicable to different users or tasks because it cannot capture the time correlation. Hill model can describe the relationship between muscle contraction and EMG, but due to the limitation of its parameter accuracy, it is not used much in engineering practice. While deep learning methods (CNN and LSTM) can automatically learn features, but the computational complexity is high and the computational resources are required, which is not suitable for low-power embedded devices. To improve adaptability, transfer learning, online learning, and minority learning have also been developed to reduce reliance on large amounts of training data and models. However, these methods are still not well developed due to the problems of real-time performance, cost of labeled data and computational efficiency, which limits their wide application in prosthesis control and rehabilitation training.

3.3. Problems of Efficient Real-Time Computing: Tradeoffs of Accuracy, Energy Consumption and Delay

To optimize the performance of the motion control system, the above three aspects must be met - high precision, low energy consumption and reduced waiting time. The use of advanced neural networks such as CNN, LSTM, or Transformer is essential for high-precision EMG signal detection. However, these methods with high computational complexity are not suitable for energy-saving embedded devices. At the same time, the control operation is also required to have strict real-time, and the traditional computing structure is often difficult to ensure accuracy and meet the requirements of reducing time delay. In order to reduce the amount of calculation, model pruning, quantization and knowledge distillation can be used to accelerate the calculation. For example, the 32-bit floating point quantity is converted to an 8-bit integer to achieve model quantization, reducing computational costs and storage space requirements. The optimization formula is as follows:

$$W_q = round(\frac{W - W_{min}}{Wmin_{max} \times (2^b - 1)}) \quad (1)$$

Where, W_q is the weight after quantization, $Wmax_{min}$ is the weight range, and b is the number of quantized bits (such as 8 bits). In addition, edge computing can reduce the data transmission time and improve the real-time performance, but it still needs to optimize the allocation of computing resources, and its delay optimization goal can be expressed as:

$$T_{total} = T_{comp} + T_{trans} + T_{sync} \quad (2)$$

Where, T_{total} is the total delay, T_{comp} is the calculation delay, T_{trans} is the data transmission delay, T_{sync} is the system synchronization delay.

Current research on neural motor control systems focuses on lightweight models, edge computing and adaptive computing framework of neural networks, but it is still difficult to take into account real-time and pertinence. How to reduce the requirement of high calculation accuracy and reduce the amount of calculation is still a key difficulty.

4. Optimization of Neural Motor Control Model Based on EMG Signals

4.1. Efficient EMG Signal Enhancement and Feature Extraction: Improve Data Quality

Because the EMG signal is vulnerable to electrode noise, motion illusion and industrial frequency interference, its quality is weakened, so the core is to effectively improve the signal and extract the feature. The main means of signal enhancement are the application of filters (bandwidth filters and wavelet denoising, etc.), normalization (such as Z-score standardization, etc.), and data enhancement (such as GAN generation adversarial networks), etc., to make the signal more robust and mitigate the impact of individual differences. For example, the mathematical expression for bandpass filtering is as follows:

$$y(n) = \sum_{i=0}^{N} b_i x(n-i) - \sum_{j=1}^{M} a_j y(n-j) \tag{3}$$

Where b_i and a_j is the filtering coefficient, and x(n) and y(n) are the input and output signals, respectively.

Signal feature extraction is an important step in the process of EMG signal classification, which mainly includes time domain statistical features such as RMS and ZC based on time domain, frequency domain analysis features such as PSD and MF based on frequency domain, and Fourier transform technologies such as STFT and WT combined with time domain features and frequency domain features. The improved feature extraction method is helpful to model stability and classification accuracy.

4.2. Optimization of Neural Motor Control Model Enabled by Deep Learning

In the development of neural motor control model, applying deep learning technology to EMG signal processing can make the neural motor control model more accurate and flexible. Traditional machine learning (such as SVM and KNN) mainly selects features manually and cannot handle complex muscle action signals well, while deep learning models (CNN, LSTM, Transformer, etc.) can enhance their discrimination and anti-interference ability by using the characteristics of model self-learning. Among them, CNN extracts time-space features and is suitable for the classification of static gestures [5]. LSTM is good at serial time features and is suitable for classification of dynamic gestures (such as changes in motion). Transformer uses an attention mechanism for time modeling and is suitable for large volumes of sub-EMG data. However, the deep learning model has some problems, such as high computational requirements and not suitable for embedded applications. Therefore, some optimization techniques such as model pruning, quantization (INT8) and knowledge distillation are used to optimize the neural network model to reduce the computation and improve the inference efficiency. If quantization can reduce computational expenditure, the optimization objective can be expressed as:

$$\hat{W} = argmin \sum_{i=1}^{N} (W_i - Q(W_i))^2 \tag{4}$$

Where W is the original weight and Q(W) is the quantized value.

4.3. Calculation Acceleration and Low Power Optimization Strategy: Improve Real-Time Performance

The main parameters of model deployment in neural motor control system are computational complexity, power consumption and real-time performance. Although the deep learning model increases the accuracy of EMG signal classification, its complex calculation, high power consumption and serious delay restrict its application in real-time control systems. In order to alleviate these problems, a variety of algorithm optimization methods are proposed. (1) Model pruning: Reduce redundant neurons, that is, reduce the amount of computation, to shorten the effect of reasoning time. (2) Quantization (int8 computation): convert floating point 32 into int8 integer quantization processing, reducing the amount of computation and storage space. (3) Knowledge distillation: the knowledge learned from the large model is transferred to the small model, which not only realizes the accuracy but also saves the calculation overhead. (4) The completion of EMG data processing on local hardware can reduce the data transmission delay and improve the response efficiency. At present, the most popular optimization methods are edge computing, model tailoring, quantization and so on. The role of each method in EMG calculation optimization is as follows:

Figure 3 shows the application ratio of different optimization methods. Among them, model pruning (30%) and quantization (25%) are used to reduce the calculation amount, edge computing (25%) improves the real-time performance, and knowledge distillation (20%) reduces the model complexity.

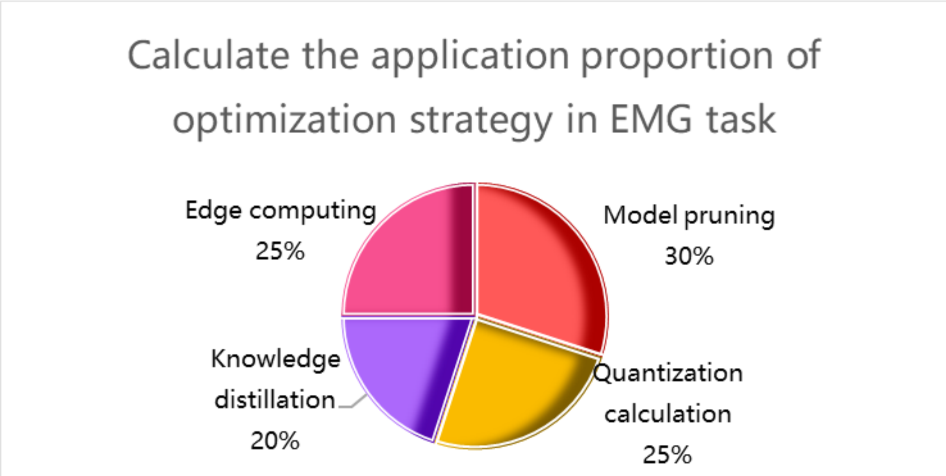

Figure 3. Calculate the application proportion of optimization strategy in EMG tasks.

5. Conclusion

Aiming at the common problems existing in neural motor control models based on EMG signals, such as signal quality, model generalization and computational efficiency, this paper tries to propose corresponding solutions from the aspects of improving signal quality, enhancing model generalization ability and improving computational efficiency. Such as using deep learning strategy to improve the accuracy of EMG signal classification, model tailoring strategy, digital compression and edge computing. Although EMG recognition technology has been widely used in prosthetics control, rehabilitation training, human-computer interaction, etc., there are still problems such as poor signal quality, individual differences, and high computing costs. In the future, multi-modal fusion information (EMG+EEG), federated learning, cloud-edge collaborative computing and other methods will be combined to improve its generalization ability and save computing costs will become the development direction. With the widespread application of artificial intelligence and the popularity of wearable devices, EMG neural motor control model will play a more extensive role in the fields of medical rehabilitation, human-computer interaction and intelligent communication.

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