1 Introduction

Stroke and other diseases may lead to lower limb motor dysfunction in patients. With the assistance of robotic technology, intelligent rehabilitation therapy can be realized to reduce the workload of clinical medical staff and improve the efficiency of patients' rehabilitation training (Kapelner et al., 2020). In the human–machine interaction between rehabilitation robots and patients, traditional human–machine interaction techniques often involve the robot passively receiving instructions, which may not be convenient for patients with motor function impairments (Zhai et al., 2017; Zhang et al., 2022). In recent years, human–machine interaction technology needs to evolve toward allowing robots to actively understand human behavioral intentions, resulting in a new type of interaction based on human biological signals.

Human bioelectric signal is the potential difference activated when the nerve signal containing human behavioral information is transmitted to the relevant organs or tissues, which is a direct reflection of human behavioral intentions (Ma et al., 2021). It is of great significance to break the human–machine barrier and realize natural human–machine interaction by decoding human bioelectric signals to recognize human behaviors, and empowering robots to understand the human body's intentions as an information medium for interaction between human beings and the outside world (Qi et al., 2020). Currently, widely studied bioelectric signals include electromyogram (EMG), electroencephalogram (EEG), electrocardiogram (ECG), and electrooculography (EOG). We focus on the surface electromyography (sEMG), which originates from the bioelectrical activity of spinal motor neurons under the control of the motor cortex of the brain, and are the temporal and spatial sum of sequences of action units produced by peripherally active motor units. Since sEMG has the advantages of being non-invasive, and simple to use, it is more suitable to be applied to the design of human–machine interaction control systems for rehabilitation robots (Xiong et al., 2021). The core technology to build the EMG human–machine interaction system is to decode the human body's motion intention through EMG signals, and the usually discussed motion intention decoding includes two categories, one is to recognize the discrete limb movements based on sEMG, such as the movements of the hand's clenched fist, extended palm, etc., and the other is to estimate the continuous joint motions based on sEMG, such as the continuous quantities of the joint moments and the joint angles, etc. In this study, we focus on healthy people and hemiplegic patients, and carry out research on sEMG-based continuous motion estimation methods for the foot and ankle area of the lower limb, which lays the foundation for future natural human–machine interaction control.

Human walking characteristics are crucial in studies targeting the continuous movement of the lower limb. Many features of the musculoskeletal system of the lower limbs implied in the human walking information. Human walking information can be used as a basis for the recognition of human movement intentions and the estimation and prediction of the human body's movements, which in turn improves the stability and accuracy of human–computer interactions with external devices, such as exoskeletons. It is also possible to compare the gait characteristics of different walking bodies, especially between healthy and patients. This enables an intelligent online evaluation of patient rehabilitation effects, such as stroke rehabilitation. Lower limb walking in healthy people is cyclic, and the inherent states of its musculoskeletal system, such as human limb properties and muscle activation states, are also relatively stable and have good model interpretability, so mechanistic models have been used to describe them in many studies (Zhang L. et al., 2021). There are also some research works that describe machine learning models such as neural networks with straightforward modeling process and unrestricted utilization of sEMG.

However, in research focused on hemiplegic patients, there are large differences in the nature of the bilateral cyclic reciprocity, with the healthy side usually experiencing weak functional decline and the affected side experiencing more severe fluctuations in cyclic information (Aymard et al., 2000; Zhao et al., 2023). The alternation of useful and useless information can lead to problems such as gradient disappearance or gradient explosion, causing loss of information (Meng et al., 2023). In addition, these weakly abled people are also prone to problems such as muscle fatigue or even spasticity, and in some cases excessive muscle tone (Zhang et al., 2019; Moniri et al., 2021), all of which will lead to a high degree of difficulty in estimating the continuity of a patient's lower extremities based on EMG signals (Sarasola-Sanz et al., 2018; Fleming et al., 2021; Zhu et al., 2022).

In machine learning network architectures for the study of continuous lower limb motion, auto-regression is a widely used method for time series prediction. It can capture the correlation and dependency of input and output sequences well, and has the advantages of simple structure, flexible order selection and easy application (Lehtokangas et al., 1996). The observations at the current time of the time series data are correlated with the historical observations. Autoregressive technologies can make use of cyclical, trend and seasonal characteristics of historical data to predict future data (Yin et al., 2023). The combination of autoregressive techniques and neural networks can effectively improve the ability of learning, understanding and forecasting of time series data (Taskaya-Temizel and Casey, 2005). A nonlinear autoregressive neural network with exogenous inputs has been proposed to model the dynamic behavior of an automotive air conditioning system (Ng et al., 2014). Combing autoregressive integrated moving average (ARIMA) and probabilistic neural network (PNN), a hybrid network model has been proposed in order to improve the prediction accuracy of ARIMA models (Khashei et al., 2012). Therefore, this article will process the sampled motion data by autoregressive technology, so that the network can fully learn the hidden features and improve the learning efficiency of the network.

In order to improve the robustness of time series signal prediction, a convolutional neural network (CNN) can be used to extract initial features from the data (Shao et al., 2024). The CNN is a specific type of feedforward neural network with a grid topology (Li Z. et al., 2021). CNN uses sparse interaction, parameter sharing and variant representation techniques to improve the feature extraction performance of convolutional operations (Li et al., 2016). Each convolution layer of CNN contains multiple convolution kernels, and each convolution checks data for sliding convolution to achieve feature extraction of time series data to obtain local features and short-term dependencies. The pooling layer performs summary statistics on the output obtained by the convolution layer (Gu et al., 2018). The local perception and weight sharing of CNN can also effectively reduce the number of weight parameters for model learning, thus improving the efficiency of model learning.