Research Article

Research on Pattern Recognition of Lower Limb Motion Based on Convolutional Neural Network

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1. Introduction

In recent years, wearable robotic equipment such as an exoskeleton has achieved extremely rapid development in military, medical, rehabilitation, and industrial fields. In the process of motion assistance, wearable robots provide corresponding assistance according to human motion patterns, which is a key factor for human-robot communion in clinical applications. Therefore, accurate human motion recognition is the basis for improving the power-assisted performance and adaptability of wearable robotic devices and is essential for achieving compliant power assistance and promoting motor function rehabilitation.

According to the different types of data acquisition equipment, the lower limb motion pattern recognition methods are mainly divided into image-based gait recognition methods and gait recognition methods based on bio-electric signals and kinematic parameters. For example, in 2009, the Artificial Intelligence, Robotics and Vision Laboratory of the Department of Computer Science and Engineering at the University of Minnesota in the United States expanded the scope of application of human motion and gait recognition systems by using image-based reconstruction and rendering methods [1]. However, the classification accuracy of this method depends heavily on the angle between the camera and the direction of motion and the training angle of view, which limits its application in actual scenes. In 2017, Castro et al. used conversion or projection to convert gait from multiple angles and proceeded with gait pattern recognition based on the walker’s local walking characteristics [2]. However, local motion characteristics cannot fully reflect the gait of subjects in different scenes and different states, so this method has a certain degree of subjectivity.

The gait recognition method based on bio-electrical signals...
and kinematic parameters is a gait recognition method that uses bioelectrical signals, leg angle signals, plantar pressure signals, and technology of multisource information fusion [3]. However, the above two types of methods have problems such as high accuracy requirements for cameras and signal acquisition equipment, large influencing factors in the experimental environment, and low accuracy of lower limb gait classification.

Surface electromyography (sEMG), as an important type of bioelectric signal [4], can reflect the body’s motion intention in real time. At the same time, due to the wearable signal acquisition method, the gait activity of the lower limbs of the human body is not limited by space, and the complex type of lower limb motion can be predicted by measuring the sEMG signals of multiple muscles. This method has the characteristics of rich information and low interference during exercise and has natural advantages in gait recognition. For example, literature [5] uses the sEMG signal as the source of gait recognition information, extracts feature values that can reflect gait characteristics, and uses machine learning for classification and recognition to improve the gait recognition accuracy. Literature [6] extracts the eigenvalues of the sEMG signal of 200 ms at the initial stage of the gait and applies the supervised Kohonen neural network algorithm to recognize the gait of the lower limbs under different road conditions.

On the other hand, with the development of artificial intelligence, gait recognition based on deep learning has been widely developed. For large-scale sEMG signal data sets, compared with traditional classifier methods, the method of using deep learning for gait recognition has higher classification accuracy. Alotaibi and Mahmood [7] proposed a deep neural network using multilayer convolution kernel subsampling layers to solve model occlusion and noise problems and improve the accuracy of gait recognition. Castro et al. [8] collected gait image data and designed a convolutional neural network using the time information in the gait sequence as training data to recognize the gait of the lower limbs.

All in all, in order to further improve the recognition rate, some researchers tend to optimize the neural network algorithm [9], but the feature processing of the sEMG signal is not carried out in advance, so the input data contains redundant data that interferes with the classification, thereby reducing the recognition rate. On the other hand, some researchers tend to process the original sEMG data and use traditional and optimized machine-learning methods to perform gait recognition [10]. However, the existing lower limb motion pattern recognition methods still face the challenges of weak recognition and classification ability, low recognition accuracy, and high demand for the amount of data of the sEMG signal of the lower limbs. Influencing factors can consider the mutual influence and constraints of data collection methods, data preprocessing, feature extraction, neural network algorithms, and other aspects in the research process. In our previous work, we explored the feasibility of using the standard deviation of the fractal dimension of sEMG signal to estimate the human motor function, and we have accumulated a lot of experience in sEMG feature extraction [11]. In this paper, aiming at the problem of lower limb motion pattern recognition accuracy, we combine deep learning methods with sEMG signal preprocessing techniques, construct a convolutional neural network with the sEMG feature set as the input, and compare the recognition accuracy and working characteristics of this method with other classification and recognition methods.

2. sEMG Signal Acquisition and Feature Extraction

2.1. Signal Acquisition. The wearable EMG measuring device Due-Pro developed by the Italian company OT Bioelectronica s.r.l. was used to collect myoelectric signals. Combined with the application background of the lower limb exoskeleton, this paper takes five movements as recognition objects: going upstairs without weight, going downstairs without weight, going upstairs with weight, going downstairs with weight, and walking upright without weight. A total of 8 muscles including the rectus femoris, lateral femoris, medial femoris, semitendinosus, biceps femoris, lateral gastrocnemius, internal gastrocnemius, and tibial anterior muscles [12, 13] were selected as the information source for the research on the lower limb motion recognition. The experimental location is the corridor of the experimental building, and the signal collection scene is shown in Figure 1. A total of 6 subjects were recruited, and each subject was required to perform 5 gait movements within one day, repeated 30 times, and the signal acquisition time for each gait movement was 1 minute. In addition, in order to maintain the unity of movements, the 6 subjects were required to perform various gaits strictly in accordance with the rhythm set by the metronome. In the same way, the signal collection work continued for 30 days; that is, a total of 6 × 5 × 30 × 30 = 27000 times of sEMG signal were collected. The sEMG data is transmitted to the computer in real time via Bluetooth for storage.

Since the effective frequency of the sEMG signal is between 0 and 500 Hz, its main energy is concentrated at 20 to 300 Hz. In order to remove high-frequency noise interference and maintain good passband and stopband characteristics, the Butterworth filter is used to filter the original signal [14], and the bandwidth of the filter is set to 20–300 Hz. Taking the sEMG signal of subject 2 walking on the ground as an example, the sEMG signals of the subject’s 8 muscles after filtering are shown in Figure 2. Among them, BF represents the rectus femoris, VL represents the lateral femoris, VM represents the medial femoris, SB represents the semimembranosus, GL represents the lateral gastrocnemius, GM represents the medial gastrocnemius, TA represents the tibial anterior, and BF represents the biceps femoris muscles. The results show that the filtering method can not only effectively filter the frequencies outside the passband but also retain the fundamental component.

2.2. sEMG Signal Feature Extraction. Common features of sEMG include time domain features, frequency domain features, and time-frequency domain features. This paper extracts the average absolute value (MAV), root mean
square value (RMS), zero crossing rate (ZC), slope rate of change (SSC), four types of time domain features and median frequency (MDF), average power frequency (MNF), and two types of frequency domain features. Compared with frequency domain features and wavelet features, the first four time domain features have the advantages of easy extraction, small calculation amount, and fast calculation [15]. The frequency domain features MDF and MNF can better show the frequency components of the sEMG signal, which is convenient for directly observing the distribution of the energy contained in the sEMG signal at different frequencies. Compared with the time domain features, the frequency domain features have better robustness [16]. Taking into account the short-term nonstationarity of sEMG, in order to ensure the continuity of features, the method of “time window + sliding step length” [17] is used for feature extraction. The sliding window width is 340 sampling points, and the sliding step length is 40 sampling points. Taking time \( K \) as an example, a sliding window with a size of 340 sampling points is selected at time \( K \), and it will be regarded as a sliding window at time \( K + 1 \) after sliding a step size of 40 sampling points. As time accumulates, the time window automatically...
meets the time ascending requirements. Figure 3 shows a schematic diagram of the step size and time window setting of the rectus femoris EMG signal when a subject goes upstairs with weight. The time domain and frequency domain feature graphs of the rectus femoris when walking on a level surface without a weight are extracted as shown in Figure 4.

2.3. Feature Data Integration and Dimension Upgrade. The extracted gait features are integrated into 30 sample data sets, of which 80% are training samples and 20% are test samples. The sample data size is $20480 \times 48$; the column vectors represent 6 features of 8 muscles, so there are 48 columns of feature vectors, and the row vectors represent the time series points of 5 samples of gait data, totaling 20480 rows. Since the row vector of the input data reaches 20480 rows, in order to avoid the problem of over-relying on computer computing power, the data set is upgraded before importing to the network model [18]. The size of the upgraded data is $n \times 200 \times 48 \times 1$, where $n \times 200$ is the total time series length of all samples.

3. Construction of a Convolutional Neural Network Model with Feature Set as Input

In order to make full use of the collected large feature data set, this paper uses a convolutional neural network suitable for big data and has a strong parameter reduction ability as the lower limb action recognition model. The convolutional neural network is a feedforward neural network. Its basic structure is composed of the input layer, convolutional layer, pooling layer, fully connected layer, and output layer. It is evolved from the multilayer perceptron (MLP). Convolutional neural networks can continuously adjust the weights between internal neurons, so as to achieve the purpose of information processing, classification, and recognition. Convolutional neural networks have the structural characteristics of local connection, weight sharing, and downsampling. The local connection characteristics make convolutional neural networks different from traditional neural networks. Some neurons between adjacent layers of the convolutional neural network are
connected, and the feature of weight sharing makes the convolutional neural network more similar to the biological neural network. These two characteristics make it possible for the convolutional neural network to reduce the network model complexity, and reduce the number of weights, thereby improving the efficiency of target recognition. Downsampling is another important concept of convolutional neural networks, also called pooling. Its purpose is to reduce the image resolution and prevent the network from overfitting.

The function of the convolutional layer is to extract the features of the image. In this layer, it usually contains multiple learnable convolution kernels. The feature map output by the previous layer performs the convolution operation with the convolution kernel; that is, the dot product operation is performed between the input item $X \in \mathbb{R}^{M \times N}$ and the convolution kernel $W \in \mathbb{R}^{C \times V \times U}$, and the corresponding threshold $b$ is added, as shown in Equation (1). Among them, $w_{u,v}$ is the value of the $u$-th row and $v$-th column on the convolution kernel $W$ and $x_{i-v+1,j-v+1}$ is the value of the $i-u+1$-th row and $j-v+1$-th column on the input data $X$, generally $U<<M$, $V<<N$. Secondly, send the result into the activation function $\delta$ (the ReLU activation function is selected in this article), and then, the output characteristic value $y(i,j)$ can be obtained, and the subscripts $(i,j)$ start from $(U,V)$, respectively. The role of the pooling layer is to sample features, which can use fewer training parameters. That is, divide the output $Y^{U,V}$ of the previous layer into regions $R_{x,y}, 1 \leq x \leq X, 1 \leq y \leq Y$, where $x_{i}$ is the output characteristic value of each neuron in the region $R_{x,y}$. This network structure selects the maximum pooling layer; that is, for a region $R_{x,y}$, the maximum value is selected as the output value of the region, thereby reducing the feature dimension of the convolutional layer output, and also reducing the degree of overfitting of the network model. The end of the network is generally 1 or 2 fully connected layers; the fully connected layer is responsible for connecting the extracted feature maps. In general, choose the cross-entropy loss function, that is, the softmax function, as the activation function, denoted by Loss; this layer maps the output of the pooling layer to the value of $a_{i} \in (0,1)$ through the softmax function, and the accumulation of these values is 1, which satisfies the probability. Finally, the maximum probability of the output node is selected, and $y_{f}$ is the final prediction target. This article classifies and recognizes 5 gaits, so there are 5 output nodes. The specific calculation method of the convolutional neural network is as follows:

$$y(i,j) = \delta \left( \sum_{u=1}^{U} \sum_{v=1}^{V} w_{u,v} \times x_{i-u+1,j-v+1} + b \right),$$

(1)

$$\delta = \max (0, x),$$

(2)

$$y_{x,y} = \max_{i \in R_{x,y}} y_{i},$$

(3)

$$\text{Loss} = -\sum_{i} y_{i} \ln a_{i},$$

(4)

This paper constructed a convolutional neural network with sEMG features as the input to recognize five gait motion patterns: up- and downstairs, up- and downstairs with load, and walking on a level surface. The constructed network model has 9 layers, mainly including 1 input layer, 3 two-dimensional convolutional layers, 2 two-dimensional pooling layers, 2 fully connected layers, and 1 output layer. The structure of the CNN has a similar structure to the LeNet originally proposed by Lecun et al. [19]. By observing the monitoring indicators in the training process such as loss and accuracy rate, the current model training status is judged, and the hyperparameters are adjusted in time to train the model more scientifically to improve resource utilization. The data-processing flow is shown in Figure 5. It is worth mentioning that due to the huge amount of data, over-fitting problems are prone to occur in the data training process, so this article adds two dropout layers to reduce the data over-fitting problem. The number of convolution kernels in the first layer of CNN is 32, the kernel size is $20 \times 3$, and the step size is 1. The number of convolution kernels in the second layer is 64, and the kernel size is 22. The number of convolutions in the third layer is 128, and the kernel size is $3 \times 3$. The pooling size of the second layer is $2 \times 1$. Use 0, 1, 2, 3, and 4 as the lower limb motion label and 5 as the wrong identification label.

Use the aforementioned training sample set to train the model and continuously iterate and update the weights and biases through error backpropagation and gradient descent algorithms. After reaching the set error or number of iterations, save the model’s cross-entropy loss (loss) and recognition accuracy (accuracy). Furthermore, the aforementioned test set is used to verify the error and accuracy of the model. The batch size of the deep learning model is 155, the learning accuracy is set to 0.01, and the number of iterations is 1000. The computer equipment used in this experiment is Windows 10 version, and the processor is i5-9400F CPU. The deep learning framework TensorFlow and the integrated development environment Spyder are used.

4. Experimental Results and Analysis of Lower Limb Motion Pattern Recognition

The confusion matrix was used to count the gait recognition results of one subject. It can be seen from Table 1 that the recognition accuracy rate of the subject’s 5 gaits is between 96.96% and 97.54%, of which the recognition accuracy rate of walking on flat ground is the highest, 97.54%, and the recognition accuracy rate of walking upstairs with weight is the lowest, 96.96%. The main reason can be considered that in the process of going upstairs with weight, the forward swing of the human legs in the air involves both the concentric and eccentric contractions of the leg muscles, and the legs exert greater force on the muscles that overcome the gravity. At the same time, the movement information of going up and down the stairs is similar, so that when the test subjects go up (down) the stairs and go up (down) the stairs with weight, the EMG signal characteristics of some lower limb muscles are similar. This increases the difficulty of classifier training, which will eventually lead to misidentification of a
small number of samples. In general, the lower extremity EMG signal feature set is used as input data for lower limb motion pattern recognition, and the gait recognition rate has reached more than 96.96%. It shows that the CNN model with sEMG features as the input is feasible for classifying lower limb motion.

Using recognition accuracy, classification time, and cross-entropy loss as evaluation indicators, the results of pattern recognition of lower limb gait with convolutional neural network method are shown in Figure 6. The red curve in the figure represents the recognition accuracy of the five gaits, and the green curve represents the cross-entropy loss of the five gaits. It can be seen from the figure that the correctly classified samples of the five gaits account for about 97.19% of the total samples, and the cross-entropy loss is about 7%. The experimental results show that replacing the original data set with the feature data set in this paper can reflect the sEMG characteristics to a greater extent, thereby making the input data of the convolutional neural network more standardized, and finally achieving a high recognition rate. In order to compare the recognition and classification effects of the method in this paper with other classification methods, this paper uses the python machine-learning library Scikit-learn to implement the traditional classifier K -Nearest Neighbor (KNN), Random Forest (RF), and Support Vector Machine (SVM) [20, 21] algorithm for 5 kinds of gait classification and identification. The classification results are shown in Figure 7. The results show that the recognition accuracies of SVM, RF, and KNN are 92.16%, 94.96%, and 88.7%, respectively. It shows that the recognition accuracy of the convolutional neural network model constructed in this paper can be higher than these traditional classifiers and has the characteristics of high recognition efficiency, good classification effect, strong generalization ability, and stable algorithm performance. At the same time, it also shows that in the research idea of human action pattern recognition based on EMG signals, in view of the large individual differences of EMG signals, short-term instability, nonlinearity, and other unfavorable factors, the method of the CNN model with EMG signal feature set as the input can make up for the limited feature extraction of traditional classifiers, so as to obtain the possibility of better recognition accuracy.

Table 2 shows the training time required for the constructed CNN network and several other methods. Table 2 shows that the average training time of CNN network is 0.23 s, and those of SVM, RF, and KNN are 1.13 s, 3.47 s, and 1.69 s, respectively, indicating that the training time of the CNN network is significantly shorter than that of traditional classification and recognition methods such as SVM, RF, and KNN. Combined with the above recognition accuracy results, it can be seen that the convolutional neural network constructed in this paper is significantly better than other traditional classifiers in terms of recognition accuracy and training time, and the recognition effect of the lower limb gait is ideal.

Further, a recognition experiment in which the filtered sEMG signal without feature extraction is directly used as
the input of the CNN has been carried out. Due to the changes in the input, the CNN structure and hyperparameters are also adjusted accordingly. The recognition results show that the recognition accuracy rate is about 76% and the training time is about 24 h. This result demonstrates the effectiveness and superiority of the method using the feature set of the sEMG signal as the CNN input for lower limb motion recognition.

This method is expected to be used for other sEMG-based motion pattern recognition fields. However, when this method is popularized and applied, it is necessary to pay attention to the influence of the signal acquisition environment, feature extraction, and network structure. First, in order to ensure the gait recognition accuracy of the lower limbs, the signal collection should be kept away from signal interference and environmental noise, and the electrode pads should be thoroughly disinfected before sticking to prevent impurities from adhering to the electrode pads, thereby ensuring the effect of signal noise reduction and filtering. Secondly, in the process of feature extraction, the time window, and the step size of the original EMG signal need to be consistent, so as to ensure that the length of each time domain feature is equal, which is conducive to the integration of feature data sets. Finally, during the construction of the neural network, the size of the convolution kernel and the number of layers of the neural network need to be set according to the dimension and size of the input data set in order to obtain the best recognition accuracy.

5. Conclusions
In view of the problems of low data volume and low recognition rate in the current lower limb motion pattern recognition technology, this paper collected the sEMG signals of five gaits of walking, going upstairs, going downstairs, going upstairs with weight, and going downstairs with weight. On the basis of feature extraction of the sEMG signal, the feature data set was optimized and integrated and a convolutional neural network with a feature data set as the input was constructed, so that a lower limb motion pattern recognition method was proposed. And the recognition accuracy and working characteristics of this method and several other classification methods were compared. The results show that, compared with the traditional method, the input feature set of this method can better represent the features of the prediction model, and the pattern recognition accuracy

![Figure 6: Gait recognition accuracy and cross-entropy loss.](image-url)

![Figure 7: Comparison of gait recognition accuracy among different classification and recognition models.](image-url)

| Models | Training time (s) |
|--------|-------------------|
| SVM    | 1.13 s            |
| RF     | 3.47 s            |
| KNN    | 1.69 s            |
| CNN    | 0.23 s            |

Table 2: Training time of various classification and recognition models.
is higher. The recognition accuracy of the five gaits are all greater than 96%, and the average training time is the least, which is 0.23 s. It can be seen that the convolutional neural network constructed in this paper is significantly better than other traditional classifiers in terms of recognition accuracy and training time. This method provides theoretical support for the improvement of lower limb motor function with rehabilitation medical robots, power-assisted robots, and other equipment.

This method uses the traditional stochastic gradient descent algorithm to train the convolutional neural network. Although a high recognition accuracy is achieved, the training time needs to be further improved. In the future, we will consider improving the learning algorithm of the network to improve the training speed and stability of the network while ensuring the recognition accuracy.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no competing interest.

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