Gait Phase Classification Based on sEMG Signals Using Long Short-Term Memory for Lower Limb Exoskeleton Robot

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Abstract. In this work, we present a Long Short-Term Memory Model (LSTMM) for gait phase classification based on sEMG signals to control the lower limb exoskeleton robot which can recognize 2 phases (Stand and Swing) of leg phases between the foot and ground. This model only needs four sEMG signals to control the lower limb exoskeleton robot helping the hemiplegia patient walking. Compared with the existing methods, the proposed model not only avoids the complex sensor systems but also enhances the accuracy of gait phase classification. The experimental results first verify the availability of sEMG data acquisition system on the lower limb exoskeleton robot made by the Shenzhen Institutes of Advanced Technologies (SIAT) by quantify the system with gold standard optoelectronic system Vicon, then show that the proposed LSTMM is significantly higher on prediction accuracy and has better robustness for gait phase classification to control the lower limb exoskeleton robot with different speeds. Finally, the maximum accuracy of LSTMM on the gait phase classification is 97.89%.

1. Introduction

1.1. Background

Every year nearly 800 000 people experience a recurrent or new stroke accounting for approximately 6.5 million stroke survivors in the U.S. alone [1]. About 80% of them experience significant impairments and require rehabilitation. The lower limb exoskeleton robot is a wearable human-robot interactive equipment tying to human legs and moving synchronously with the human gait. Hence, the gait phase classification is a significant study to help stroke walking easily. However, few studies classify the gait phase from sEMG signal [2]. As reviewed in [3], majority of the studies devoted to recognizing gaits for the lower limb exoskeleton robot have been performed using kinetics and kinematics data (gyroscopes, force detectors and foot inertial sensors) during locomotion. In this work, we will use the sEMG signals to classify the phase of gait cycle into two phases—Stand (ST) and Swing (SW) [4]. sEMG is acknowledged as a non-invasive approach, specifically suitable to monitor muscle activity during walking [5]. sEMG signals are typically coupled with signals able to provide the synchronization of the gait cycle, such as joint angles, to control the lower limb exoskeleton robot.
Consequently, many researchers have a growing interest in using the sEMG signals to accurately classify the gait phase to control the lower limb exoskeleton robot helping walking problem people.

1.2. Related works
In recent years, with the development of machine learning and deep learning techniques, various machine learning algorithms, such as linear discriminant analysis (LDA) [6], multilayer perceptron (MLP) [7] and SVM [8] have been used for classification problems. Specifically, Joshi et al. [6] adopt LDA to separate different phases of a gait cycle with the EMG signal data of the lower limb exoskeleton. [7] employs the MLP, which has the advantages of build non-linear fits, to classify the gait phase obtaining satisfactory results. AS for SVM, Ziegler et al. [8] use the theory of SVM to solve the classification of ST and SW phase during healthy human gait based on the muscle.

1.3. Motivation
However, all of the above methods [6]-[8] have emerged drawback on time series. Such as bigger memory spending and lower accuracy on long time series. With the development of machine learning algorithm, Long Short-Term Memory (LSTM) have demonstrated ground-breaking performance on classify, process and predict time series. For example, LSTM has been widely applied in handwriting recognition, speech recognition and image generation for gait phase detection. Due to the LSTM architecture has memory cell, it can utilize current and previous information to prediction or classification. Therefore, taking advantage of LSTM to classify the gait phase is a new direction.

Motivated by the above work, this work propose a Long Short-Term Memory Model (LSTMM) for gait phase classification based on sEMG signals to control the lower limb exoskeleton robot which can recognize ST and SW phase of leg phases between the foot and ground. The proposed model is based on [9], where Ding et al. apply the LSTM to detect and discriminate gait phase based on single Inertial Measurement Unit (IMU). Inspired by the [9], we first attempt to apply the LSTM to solve the problem of gait phase classification based on sEMG in the lower limb exoskeleton robot. Compared with the previous studies, our specific contributions are summarized as following:
(1) We propose an LSTMM for gait phase classification based on sEMG signals to control the lower limb exoskeleton robot helping the people who have walking problem.
(2) In our model, we capture the signals from four muscles of the lower limb using sEMG signal acquisition system. Only four muscles sEMG signals can detect phases of walking in contrast to [9].
(3) The proposed LSTMM based on sEMG signals is not only higher on prediction accuracy but also has better robustness for gait phase detection to control the lower limb exoskeleton robot under different speed.

2. Methods on gait phase classification

2.1. Long Short-Term Memory
Fig. 1 shows the basic architecture of an LSTM memory block with one memory cell. Where $\sigma$ denotes the gate activation function, which is generally the sigmoid function; $g$ represents the input activation function which is usually the tanh function; $h$ represents the output activation function that is usually the tanh function. At time $t$, the input gate calculates the input message of LSTM unit $i_t$, forget gate calculates the information $f_t$ left by the LSTM unit, output out calculates the LSTM unit output information $O_t$, which are defined as:
Figure 1. LSTM memory block and the Gait phase classification of LSTMM

\[
i_t = \sigma(W_{ix}x_t + W_{ih}h_{t-1} + W_{ic}c_{t-1} + b_i)
\]
(1)

\[
f_t = \sigma(W_{xf}x_t + W_{fh}h_{t-1} + W_{fc}c_{t-1} + b_f)
\]
(2)

\[
o_t = \sigma(W_{ox}x_t + W_{oh}h_{t-1} + W_{oc}c_{t-1} + b_o)
\]
(3)

Where \(x_t\) denotes the input, \(h_t\) of time represents the hidden layer state of \(t\) time, \{\(W^*\}\) represents the weight matrix of LSTM unit, and \{\(b^*\}\) represents the bias item of LSTM unit. The \(c_t\) updates formula and output of the whole unit \(h_t\) are as follows:

\[
c_t = f_t c_{t-1} + i_t g(W_{ix}x_t + W_{ih}h_{t-1} + b_i)
\]
(4)

\[
h_t = o_t g(t_c)
\]
(5)

Owing to the multiple LSTM cells can be stacked for more expressive power. In the process of normal walking, the pose angle of hip and knee joint and the sEMG signals are obtained, so the gait of human body is analyzed and divided. As shown in Fig. 1, the LSTM neural network structure is divided into 1 layer input layer, 1 layer hidden layer and 1 layer output layer. The input layer is composed of 4 signals, the number of neuron nodes in hidden layer is 128, it uses relu as the activation function, the probability of signals not being set to 0.5 by dropout, the method of using dropout can make the LSTM network model more robust and avoid the problem of over-fitting. The softmax layer is selected as the output layer composing of two nodes, which are divided into two gait categories.

2.2. Support Vector Machine

An outline of the SVM classification algorithm is described as follows: let \(x_i = R^n, i = 1,...,m\) be data points of a training data set in an \(n\)-dimensional feature space. Define a vector \(w\), a scalar \(b\) and a vector of labels \(y \in R^m\), \(y_i \in \{1,-1\}\) with \(y_i = 1\) for samples and \(y_i = -1\) for samples, such that

\[
y_i(w^T x_i + b) \geq 1 - \varepsilon_i
\]
(6)

The slack variable \(\varepsilon_i \geq 0\). Defining \(y_i(w^T x_i + b) - 1 = 0\) on the class borders, the margin \(d\) between the classes can be calculated as \(d = 2/w\). The corresponding constrained optimization problem is then

\[
\min \frac{1}{2} ||w||^2 + C \sum_i \varepsilon_i
\]
(7)

where weight factor \(C > 0\).
The performance of SVM classifier relies on the choice of regularization parameter C. The value of C in this part is set to 1. During gait phase classification, the training labels are assigned to two activities as well as to the transitions between these activities.

2.3. Multi-Layer Perceptron
Multilayer perceptron (MLP) can project the input to a linear separable space with a particular set of weight values. For the lower limb exoskeleton gait phase classification based on sEMG signals, the input is the sEMG signals. Signals \((V_Q, V_H, V_T, V_G)\) pass from the input layer through the hidden layers to the output layer. The output of MLP is used to control the movement of exoskeleton robot.

3. sEMG signals acquisition

3.1. sEMG signal acquisition process
A 16 channels wireless sEMG signals acquisition device that used in our experiments is made by Biometrics (US) shown in Fig. 2. Out of the available 16 channels, 4 channels are used for left leg with 1 channel corresponding to sEMG data from one muscle. Fig. 2 shows the activity of four muscles (Quadriceps, Hamstring, Gastrocnemius and Tibialis Anterior) of the lower limb that is captured during the gait cycle. And the electrodes are located according to the guidelines of the expert.

![Figure 2. Biometrics device and the position of sEMG acquisition](image)
For rehabilitation of hemiplegia patients, obtaining the real-time sEMG signals can control the exoskeleton robot exactly classifying 2 phases of leg phases between the foot and ground. The SIAT exoskeleton robot has power assist mode and zero-torque mode. The clutches are designed on each joint for switching between two modes. The power-assist mode offers enough torque to let wearers walk with the crutches to maintain balance. In zero-torque mode, the wearers walk following their own will, and the exoskeleton offers torque as need. This work is based on the zero-torque mode.

3.2. sEMG Data Source and Gait Data phase division
Six healthy and never suffered gait dysfunctions male testers are recruited in the experiments for training classifiers. The purpose and the procedure of the data collection are understood by the testers. The detail information of the testers is shown in Table 1. Each tester wears the SIAT exoskeleton robot set in zero-torque mode and walks in their comfortable way for a while on the AMTI (US) force platform under different speed to obtain the sEMG signals data. Testers are required to walk on one minute 2 times with their normal walking speed while the SIAT robot controller records the sEMG signal acquisition device data by a Bluetooth device. Finally, we get the sEMG samples data in Table 1.
It’s easy to find that the phases of SIAT exoskeleton robot can be classified into ST and SW phases.

3.3. Assigning labels process
The hip joint angle and knee joint angle are used to assign labels to the sEMG data. The threshold of the hip joint angle and knee joint angle to classify the gait phase is calculated as
\[ \tau = \theta_{\text{min}} + \alpha (\theta_{\text{max}} - \theta_{\text{min}}) \]
where, \( \tau \) is the joint angle threshold of the walking gait, \( \theta_{\text{max}} \) and \( \theta_{\text{min}} \) is the max and min value of the joint angle, \( \alpha \) is the coefficient that represents the percentage of threshold. \( \alpha \) is from 0.2 to 0.25 in table 1. While the hip angle greater than threshold and the knee angle below the threshold, the gait phase is SW. Other cases are ST.

4. Gait phase classification results
4.1. The availability of sEMG data acquisition system
To validate the output of the sEMG data acquisition system, two randomly selected healthy testers are asked to walk at least 1 minute under speed of 2.0 km/h on the AMTI force platform with retro-reflective markers placed on the SIAT lower-limb exoskeleton robot under Vicon environments shown in Fig. 3. Three Vicon cameras are used to track the trajectories of the markers while the sEMG data output signals are recorded. Based on the marker trajectories the reference gait phase signal generating. The reference signal is compared to the measured sEMG data acquisition system output in Fig. 4. A typical example of the hip angle signal, knee angle signals, and sEMG gait data acquisition system output signal and labels recorded during the walking of tester are shown in Fig. 4. Synchronized Vicon measurements of the (hip and knee) marker positions in the horizontal direction are shown in the Fig. 3. Due to the sampling frequency of the sEMG is set to 1000 Hz. Sampling frequency of the Vicon motion capture system is 100 Hz. Thus, 1 sample of angular data corresponds to 10 samples of the sEMG data according to [8]. A comparison between the reference angle signal (red line), which is generated by the hip and knee markers trajectories, and the sEMG data acquisition system output signal (blue line) is shown in the Fig. 4. The sEMG data acquisition system output correlated well with the reference gait phase signal for all trials. A gait cycles with walking speed 2.0 km/h indicate that the sEMG data acquisition system of the two gait phases relative to the reference signal is synchronization.

![Figure 3. Vicon environments](image-url)
Figure 4. The comparison of the sEMG data acquisition system with Vicon

4.2. The availability of sEMG data acquisition system

Next, we begin to classify the gait phase by LSTM, SVM and MLP. Defining input $x$ as

$$x = [V_Q, V_H, V_T, V_G]$$

(9)

where $V_Q, V_H, V_T$ and $V_G$ denote the EMG signal of left quadriceps, hamstring, gastrocnemius and tibialis anterior, respectively. To verify the robust of the above models on gait phase classification to control the SIAT exoskeleton robot, we analyse the walking speed of 1.5km/h, 2.0km/h and 2.5km/h. Each speed all selects 3000 valid samples. All of the models use the same train and test set to test the performance of the models. The train set account for 80% and the test set take up 20%.

1) LSTM: Fig. 5(a) presents the gait phase classification results of LSTM, where the gait phase prediction accuracy on 1.5km/h, 2.0km/h and 2.5km/h are 97.61%, 97.89% and 97.75%, respectively.

2) SVM: Fig. 5(b) shows the gait phase classification results of SVM, where the gait phase prediction accuracy on 1.5km/h, 2.0km/h and 2.5km/h are 94.83%, 95.11% and 94.55%, respectively.

3) MLP: The gait phase classification results of MLP is shown in Fig. 5(c). We can see that the average accuracy walking on 1.5km/h, 2.0km/h and 2.5km/h are 93.06%, 93.33% and 92.61%.

Figure 5. The gait phase classification results of LSTM, SVM and MLP
### Table 2. Model Results.

| Speed | LSTM   | SVM    | MLP    |
|-------|--------|--------|--------|
| 1.5km/h | 97.61  | 94.83  | 93.06  |
| 2km/h  | 97.89  | 95.11  | 93.33  |
| 2.5km/h | 97.75  | 94.55  | 92.61  |

After above works, the best results of LSTM, SVM and MLP are shown in Table 2. From Table 2, the proposed LSTMM is shown to be robust for gait phase classification to control the lower limb exoskeleton robot under different speed in precision. The maximin accuracy of the gait phase classification is walking with 2km/h which is also the normal speed of the stroke people.

### 5. Conclusion

This work presents an LSTMM for gait phase classification based on sEMG signals to control the lower limb exoskeleton robot which can recognize ST and SW phases of leg phases between the foot and ground. Compared with the existing methods, our model just needs four sEMG signals to control the lower limb exoskeleton robot assisting the hemiplegia patient to walk. The experimental results show that the proposed model is not only higher on prediction accuracy but also has better robustness for gait phase classification to control the lower limb exoskeleton robot under different speed.

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