BP–AR-BASED HUMAN JOINT ANGLE ESTIMATION USING MULTI-CHANNEL SEMG

Lina Tong,*,** Feng Zhang,** Zeng-Guang Hou,** Weiqun Wang,** and Liang Peng**

Abstract

Human motion estimation by surface electromyogram (sEMG) is one of the most important human intention recognition methods for active rehabilitation training. This paper proposes a back propagation (BP) neural network and autoregressive (AR) model based real-time sEMG–joint angle estimation method. To reduce the time delay, a moving Butterworth filtering method is designed to filter the lower limb multi-channel sEMG signals. Then correlation analysis between sEMG signals and joint angles is made to reduce redundant channels. A first-order BP neural network is used to build the mapping relationship between multi-channel sEMG signals and joint angles, then the approximated angle by BP model is adjusted by the AR de-noising model, which describes the angle variation features of the given training mode to improve the accuracy and continuity. To validate this method, five able-bodied subjects participated in cycling exercise experiment, and the angle estimation results show that this method presents a good performance on real-time computation, accuracy and continuity.

Key Words

sEMG–joint angle estimation, rehabilitation, moving Butterworth filtering method, BP neural network, autoregressive (AR) model

1. Introduction

Stroke, a kind of medical emergency, can cause permanent central neurological damage, complications and death. It is the leading cause of adult disability and the second leading cause of death worldwide [1]. More than 80% of strokes occur in the elderly over 65 years old [2], and disability affects 75% of the stroke survivors [3]. With the acceleration of population aging process, the stroke-related disability has brought significant financial and labour burden to society and family. The functional rehabilitation of central nervous system relies on the frequent uses of their motor functions and can be generated by long-term active movements. Researches show that rehabilitation trainings have very positive effects on improving the recovery of nervous system and preventing secondary complications after stroke [4], especially by the active training modes [5], [6], which uses human active motion intention as references for control information. Thus, accurate, stable and real-time human motion intention recognition is essential to realize patients’ active movements-based training system.

During human motor activities, skeletal muscles voluntarily contract; micro-volt level bioelectrical potential is generated within muscle cells and can be measured from the surface of skin. The procedure of measuring neuromuscular system activities from skin is called surface electromyogram (sEMG) and can be non-invasive [7], [8]. As sEMG signal shows the instruction of neuromuscular system motor function real-timely and objectively, it can be used to evaluate the functional status of skeletal muscles and assist in neuromuscular training and rehabilitation [9]. This work focuses on providing a reliable real-time human limb motion estimation method using sEMG for active rehabilitation training system.

Nowadays, in active rehabilitation training research, the training functions are programmed according to human active motion intention, and sEMG signal is one of the main kinds of biosignals used for human motion pattern recognition, such as limb postures [10]–[13], muscle force [14]–[16], or motion state estimation (such as joint angle, torque) [17]–[20], etc. First, sEMG is used as switching signals to recognize the kind of activities and then program the training system to complete a fixed motor trajectory [12]. Thus, it can be used for prosthetic control, too. For instance, Naik et al. [11] used sEMG from four forearm muscles and the twin SVM method to classify seven kinds of movements of fingers and wrist flexion, and achieved 84.83% sensitivity and 88.1% specificity. Momen et al. [12] used fuzzy C-means cluster to partition forearm sEMG feature space and recognized four and five kinds of hand movements with average accuracies of 92.7 ± 3.2% and 79.9 ± 16.8%, respectively. This kind of sEMG application usually has relatively higher recognition accuracy; however,
because the robot arms’ trajectories are fixed according to motion kinds, it cannot satisfy the variety of human movements. The mathematical models for sEMG–muscle force are always very complicated [14]–[16], some parameters are different according to body physical conditions (such as muscle fatigue, fat content) and environments, and also hard to measure, thus the practical applications are limited.

Using measured sEMG to estimated human joint motion states real timely, so as to plan the motion trajectory of rehabilitation robot is another way to realize active training; such as building the mapping relationship of “sEMG–joint angle” [30]. There are some advances in this research field recently. For instance, Shirraro et al. [17] used neural network models to predict finger joint angles based on sEMG of extensor digitorum superficialis muscle during the flexion–extension cycle. The experiment showed a relatively small RMS (root mean square) error; however, it also caused time delay by 200 ms. Due to the serious disturbance and interference with the recorded sEMG signals, the time delay always seems to be unavoidable [16]–[18] and then brings negative influence to real-time control. Our team tried to use a 20-order BP neural network model to describe the relationship between sEMG time series and human joint angles [19], and the average RMS error for treadmill exercise is about average 5°–6° for able-bodied subjects without considering the time delay.

Besides the angle estimation accuracy and real-time requirements, the control effect of rehabilitation training also relies on the continuity of the estimated angle signal. The motion trajectory of human body is continuous and smooth. However, because the serious interference to recorded non-stationary sEMG signals, the error of some estimated angles may be too large to satisfy the requirement of the continuity of human movements. As for the rehabilitation control systems, the discontinuous angle information inputs will cause negative control effect, such as mechanical system trembling, or worse, cause safety problem: if the instantaneous velocity exceeds a certain extent, it will be harmful to human body. Here, we call the estimated angles that make the instantaneous angle velocity exceeds the safe level singularity point. Thus, the singularity removal is important. Unfortunately, previous researches haven’t taken the continuity of angle estimation into account. Hence, it is one motivation of this study: improving the continuity of the estimated angles but do not consume too much time.

For some parts of human body, the training modes of some movement styles have more positive effects on the rehabilitation of motor functions than the others [19]. Previous researches showed that the cycling and treadmill training plays a more effective role on gait function rehabilitation [20]. Therefore, finding out the joint angle variation features of some given training modes (always assigned by the rehabilitation physicians), and using them to adjust the estimated joint angles, can be another way to improve the accuracy and continuity.

Based on the above motivations, this paper proposes a new sEMG–joint angle estimation method based on BP neural network and AR model to utilize their advantages to improve the angle estimation accuracy, continuity and time consumption, and we call it BP–AR method. The BP model is used to map the relationship of multi-channel sEMG features and human joint angles, while the AR model describes the variation features of joint angle during some given training modes and is used to adjust the angle estimation results, so as to improve the accuracy and continuity. As to reduce the time delay, a moving But-terworth filtering method is designed in feature extraction process. To validate the effectiveness of this method, five able-bodied subjects participated in the experiment with cycling exercises, and the knee joint angles are estimated with an average RMS error of 4.27°, maximum angle velocity of 371.2°/s, with time delay of 10–15 ms. This paper firstly took account of the angle continuity and took simple but practical measure to improve it. Compared to traditional artificial neural network (ANN) method, the BP–AR method proposed in this paper showed a good performance on angle estimation accuracy, continuity and real-time computation.

This paper is organized as follows: Section 2 introduces the experiment of sEMG information acquisition. Section 3 introduces the method including sEMG signal processing, BP model and AR model structure. Section 4 shows the experimental results. And this work is concluded in Section 5.

2. Information Acquisition

The experiment of this work is based on cycling exercise with a low speed of 16–20 cycles per minute, which is one of the most typical lower limb exercises for stroke patients. Here, multi-channel sEMG signals from the main muscle groups of lower limb and knee joint angles are obtained simultaneously. Then, through correlation analysis of sEMG signals and angles, the channels of sEMG for angle estimation are determined.

To acquire data samples, the FlexComp InfiniSyst em produced by Thought Technology Ltd., Canada (sensitivity: <0.1 \( \mu V_{\text{RMS}} \), accuracy: \( \pm 0.5 \mu V_{\text{RMS}} \pm 4\% \), raw data recording sampling rate: 2,048 Hz), was used to obtain multi-channel sEMG signals from lower limb muscles. And the InclinoTrac System (Thought Technology Ltd., Canada, sensitivity: 0.1°, accuracy: 1.0°) was used for knee joint angle data acquisition. The two systems worked simultaneously. As this data acquisition system has 10 channels, three of them are used to collect and improve joint angles, thus the other seven channels can be used to collect multi-channel sEMG signals.

The location of sEMG sensor electrodes may have a significant effect on the recognition of human motions [21] and should be concerned before experiment. To study the relationship between lower limb multi-channel sEMG and knee angles during cycling exercise, the selected muscle groups must satisfy three requirements:

1. They should be superficial, as surface EMG signals are measured.
2. Their skin contacted surfaces are big enough to stick sEMG sensor electrodes.
3. They can affect knee flexion during their contraction or expansion.
Table 1
Description for Selected Muscles and Their Motion Functions [24]

<table>
<thead>
<tr>
<th>Superficial Muscle Group</th>
<th>Motion Functions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thigh</td>
<td></td>
</tr>
<tr>
<td>Rectus femoris (RF)</td>
<td>Flex the thigh at the hip joint and extend the lower leg at the knee joint.</td>
</tr>
<tr>
<td>Vastus lateralis (VL)</td>
<td>Perform expansion of knee joint.</td>
</tr>
<tr>
<td>Biceps femoris (BF)</td>
<td>Perform knee flexion and hip extension. But it is a weaker knee flexor when the hip is extended and hip extender when the knee is flexed.</td>
</tr>
<tr>
<td>Semitendinosus (ST)</td>
<td>Extend the hip joint and flex the knee joint, rotate the tibia on the femur when the knee is flexed and medially rotate the femur when the hip is extended.</td>
</tr>
<tr>
<td>Crus</td>
<td></td>
</tr>
<tr>
<td>Tibialis anterior (TA)</td>
<td>Perform dorsi-flexion and inversion of the ankle.</td>
</tr>
<tr>
<td>Gastrocnemius med. (GM)</td>
<td>Plantar flex the foot at the ankle joint and flex the leg at the knee joint, especially in large contractions and rapid development of tension. (The functions of Gastrocnemius med. and Gastrocnemius lat. are similar, so only GM is selected.)</td>
</tr>
<tr>
<td>Soleus muscle (SM)</td>
<td>Bent crus, plantar flex of the foot, lift heel, fix knee, maintain standing posture, etc.</td>
</tr>
</tbody>
</table>

Figure 1. The location of sEMG sensor electrodes.

Therefore, these seven main superficial muscle groups of left lower limb are taken into account in the experiment, according to their main motion functions, as given in Table 1 and Fig. 1. (The original drawing is from [25].)

To acquire the best readings, the Ag/AgCl electrodes were placed on the muscle bellies with the positive and negative electrodes parallely located to the muscle fibres. The arrangements for sEMG electrodes and angle sensors are shown in Fig. 2.

In this work, five able-bodied student volunteers (four males, one female, 28 ± 4 years old, and 170 ± 7 cm heights, weight 68.8 ± 8.4 kg) took part in the experiment to acquire data samples. The subject selection criterion is that the subcutaneous fat in the leg must be moderate, not too much or too little, as the fat can affect the sEMG recording. During the experiment, both of the two legs worked together to complete cycling exercise, hence the contribution to the movement of each leg is the same. One set of data samples is shown in Fig. 3.

3. BP–AR-based Angle Estimation Method

3.1 Signal Sampling and Feature Extraction

3.1.1 Sub-sampling and Feature Extraction in Time Domain

In this work, the feature extraction process is start from analysing the amplitude features of sEMG, as the amplitude of sEMG signal presents the magnitude of muscle force [7]–[9]. And to improve the real-time performance of angle estimation, the features are extracted in time domain. There are two most popular methods [18], [22]: averaging method and RMS method.

The RMS of sEMG amplitudes is defined as:

\[
RMS_{sEMG} = \left[ \frac{1}{T} \int_{t}^{t+T} sEMG^2(t)dt \right]^{\frac{1}{2}}
\]
Figure 3. One set of raw data multi-channel sEMG samples (10s, four cycles of treadmill exercise), which have been amplified.

where $sEMG(t)$ is the amplitude of single channel sEMG signal and $T$ should be the sampling period after sub-sampled. According to the low-frequency behaviour of human movements, the sub-sampled frequency is set 128 Hz, i.e., $T = 16 \cdot (1/2,048) s = 7.8125 ms$.

In contrast with the mean value of $sEMG(t)$, $RMS_{sEMG}$ can not only reflect the signal amplitude variation in time domain, but also the muscle loads and intrinsic relationship of muscle physiological and biochemical process [22]. Hence, it can be used to analyse the muscle active state in real-time non-invasively. Here, the feature of RMS values of sEMG amplitudes is extracted, and the sub-sampling procedure can be completed at the same time.

However, due to the serious interference, the signal curves after sub-sampling and RMS feature extraction still vibrate violently (Fig. 4).

3.1.2 Moving Butterworth Filtering Method

The recorded signals from sEMG sensors consist of both sEMG and noises. There are not only the noises caused by hair, skin, fat, and other physiological factors, but also power line interference, DC bias, baseline noise, and so on. Accordingly, the sEMG waveforms after sub-sampling are still non-linear, non-stationary. To improve the angle estimation results, signal filtering is necessary, and the filtering method should make the frequency response as flat as we need in the passband. However, after the signal filtering, the filtered sEMG signal will delay from the original signal inevitably in time domain and then causes time delay of angle estimation results. To reduce the time delay, a moving Butterworth filtering method is designed here.

Butterworth filter is a kind of signal processing filter designed to have as flat a frequency response as possible in the passband. The gain $G(\omega)$ of an $n$-order Butterworth low pass filter is given in terms of transfer function as:

$$G^2(\omega) = |H(j\omega)|^2 = \frac{G_0^2}{1+(\omega/\omega_C)^{2n}}$$

where $n$ is the order of the filter, $\omega_C$ is the cut-off frequency, and $G_0$ is the DC gain (gain at zero frequency).

Although it is referred to as a maximally flat magnitude filter, it will cause time delay inevitably for filtering finite-length discrete signal in practical application like other filters. The larger of $n$, the more time delay; the less of $n$, the less flat of the filtered signal. To make the filtered signal flatter with less time delay, a moving Butterworth filtering method is designed. The main idea of this method is to utilize the signal segment before current time to get the filtered signal at current time, so as to reduce the time delay in signal filtering process. The current time is denoted as $t$, and the filtering process is shown in Fig. 5.

The filtering method can be realized by four steps.

1. Use a sliding window (length = $L$ and $L \geq n$; and the time period equals to sEMG signal sub-sampling) to get a segment of original signal from $(t - L + 1)$ to $t$.

2. Filter this signal segment with Butterworth filter to obtain the filtered signal series.

3. Get the element at the end of the filtered signal series and make it the current filtered signal element.

4. Move on the sliding window with one step, so as to get the filtered signal series without time delay.

This is a time-delay-free filtering method. The comparison experiment results of Butterworth filtering and moving Butterworth filtering show the advantage of this method.
method. In Fig. 6, we can see that, in contrast to Butterworth filtering method, the moving Butterworth filtering method can not only flatten the original signal, but also reduce the time delay significantly. Considering the continuity of filtered signal, we calculate the mean and maximum absolute value of first derivative of Butterworth filtered signal and moving Butterworth filtered signal respectively: mean value of the former is 0.1483, the latter is 0.1451; the maximum value of the former is 1.4276, the latter is 1.4063. Hence, the moving Butterworth filtering method can flatten the original signal well. In the experiment section, we will validate its influence on angle estimation results.

As we can see that, using this method, the time delay equals to 1 time period of the sliding window and is caused by data acquisition:

\[
\text{Time delay} = T = 16 \cdot (1/2.048) \text{s} = 7.8125 \text{ms}
\]

### 3.1.3 Feature Reduction

To improve the efficiency of angle estimation algorithm and reduce the time delay further, it is necessary to remove the redundant channels from the seven-channel sEMG. One of the simplest and widely used feature reduction methods is analysing the correlation coefficient between the signals to be estimated and the target signals.

The correlation analysis is used to determine whether the values of two variables are associated. The correlation coefficient between one channel of filtered sEMG feature series \( S = \{s_i\} \ (i = 1, 2, 3, \ldots) \) and its time corresponding knee angle series \( A = \{a_i\} \) is:

\[
\rho_{S,A} = \text{corr}(S, A) = \frac{E[(S - ES)(A - EA)]}{\sigma_S \sigma_A}
\]

where \( \text{corr} \) is a widely used notation for the correlation coefficient, \( E \) is the expected value operator, and \( \sigma \) is the standard deviation operator.

In Table 2, the mean correlation coefficients of filtered sEMG signal and knee angle signal from all the subjects are calculated. The correlation coefficient values can be used as the selecting rule to determine the channels of sEMG to be analysed. The higher the \( \rho_{S,A} \) is, the more correlated \( S = \{s_i\} \) and \( A = \{a_i\} \) are. Therefore, sorting the correlation coefficients in Table 2 can help to select channels. Generally, when the correlation coefficient between two variables is higher than 0.8, it is considered that they are well correlated with each other. Therefore, we choose RF, VL channel, and SM channel as a redundancy channel (for more information) to study the sEMG–knee joint angle estimation method.

It is worthwhile to note that the result of feature reduction here is based on the signal processing method (e.g., the moving Butterworth filtering method) in this paper. When the signal processing method changed, the calculated correlative degree values may be different.

### 3.2 BP-based sEMG–Joint Angle Estimation Method

The ANN is a mathematical model used to model complex relationships between inputs and outputs or to find patterns in data [28]. One kind of the most widely used ANN is BP neural network, whose basic function is the approximation of non-linear continuous rational function and has been used for sEMG recognition [16]–[18].

The problem of multi-channel sEMG–knee joint angle estimation can be described as follows:

- The multi-channel sEMG signals can be denoted as the input vector \( U \). As channel RF, VL, and SM signal have been selected above, \( U = [u_{RF}, u_{VL}, u_{SM}] \).
- The knee joint angle signal acquired simultaneously with \( U \) can be denoted as the output variable \( y \).
- The relationship between input vector \( U \) and output variable \( y \) can be a non-linear system stated by discrete function \( f \). Suppose that at time \((k + 1)\), the output \( y \) depends on the past output values from time

<table>
<thead>
<tr>
<th>Channel</th>
<th>RF</th>
<th>VL</th>
<th>ST</th>
<th>BF</th>
<th>TA</th>
<th>SM</th>
<th>GM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean correlation coefficient</td>
<td>0.8913</td>
<td>0.9021</td>
<td>0.6272</td>
<td>0.2677</td>
<td>0.2095</td>
<td>0.7635</td>
<td>0.4576</td>
</tr>
</tbody>
</table>
Figure 7. The structure of BP neural network.

\[(k-n+1) to k, and the past input values from time (k-m+1) to k, m,n \in [1,2,\ldots,k].\] Therefore, the system input–output function is:

\[y(k+1) = f(y(k), \ldots, y(k-n+1), U(k), \ldots, U(k-m+1))\] \hspace{1cm} (4)

To approximate function \(f\), a three-layer BP neural network is built, and the structure is shown in Fig. 7, where \(W_{in}\) and \(W_{out}\) are the weight matrixes of hidden layer and output layer respectively; \(b_{in}\) and \(b_{out}\) are the threshold value vectors of the hidden layer and output layer, respectively.

- The input layer, as three channels of sEMG signal are taken into account, the amount of nodes is \(3m\); where \(m\) is the order of BP model. To improve the computational efficiency and reduce time consumption, here 1 order model is selected: \(m = 1\).
- The middle layer (the hidden layer), the non-linear “tansig” function is used as the transition function, and the amount of nodes is \(n\). The value of \(n\) has a great influence on the approximation accuracy and can be determined by experiment. As the previous work of our team had shown in [18] that the optimal number of neural node is 20, here \(n = 20\) is set.
- The output layer, the linear “purelin” function is used, and the amount of node is 1, as the output value is estimated knee joint angle: \(\hat{y}\).

Theoretically, this kind of ANN can approximate any non-linear function on a compact set. The model training aims at approximating the mapping relationship of function \(f\), denoted as \(\hat{f}\), i.e.,

\[\hat{y} = \hat{f}(u_{RF}, u_{VL}, u_{SM})\] \hspace{1cm} (5)

In practical applications, due to the limits of data samples, noises and network training methods, there are still errors between sensor detected angle \(y\) and the approximated angle \(\hat{y}\). The mean RMS error is usually used to evaluate the approximation accuracy:

\[e_{RMS} = \left[ \frac{1}{\text{len}} \sum_{i=1}^{\text{len}} (\hat{y}_i - y_i)^2 \right]^{\frac{1}{2}}\] \hspace{1cm} (6)

where \(\text{len}\) is the length of angle series \((y)\).

Figure 8. The matching degrees of different-order AR models.

3.3 AR-based Angle De-noising Method

As the recorded sEMG signal always contains many kinds of noises, the serious interferences may pass through the signal processing and angle estimation procedures and shows errors to the estimated angle signal \(\hat{y}\). According to joint angle variation features of rehabilitation motion modes, adjusting the estimated angle series \(\{\hat{y}_i\}\) to reduce noises can improve the final accuracy and continuity of the angle estimation method. Here, an AR model–based joint angle de-noising method is proposed to improve the angle estimation accuracy and continuity. That is reducing the mean RMS errors and removing the singularity points as far as possible.

AR model is a type of random process, which is one of a group of linear prediction formulas that attempts to model and predict the output of a system based on the previous outputs series [23]. The \(p\) order AR model \(\text{AR}(p)\) is defined as:

\[X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t\] \hspace{1cm} (7)

where \(\varphi_i (i = 1, \ldots, p)\) are the parameters of model, \(c\) is a constant that can be omitted for simplicity, and \(\varepsilon_t\) is white noise.

In this paper, the AR model is used to describe the joint angle variation features during the given kind of rehabilitation training movement and adjust the estimated angles that go beyond the deserved features range (such as the maximum angle velocity). The joint angle variation features during human movements show less complex. For example, for the knee joint angle signal during cycling exercise, it is continuous, smooth and sine wave like as shown in Fig. 4 and can be described by an AR model. Figure 8 shows the mean matching degrees between different-order AR models and knee angles during cycling exercises from every subject, and it indicates they match very well. The higher of the order \(p\), the higher the matching degree, but also more time consuming in application. When the order \(p > 5\), the matching degree increment gets lower, hence, to make it simple to apply, we take AR(5) to describe the features of joint angle variation:

\[y_t = \sum_{i=1}^{5} \varphi_i y_{t-i}\] \hspace{1cm} (8)
During rehabilitation training process, the joint angles cannot change suddenly, as human movements are continuous and cannot change suddenly, either. From Section 3.1, we can get the recognition period of estimated joint angle signal is $T_\theta = 7.8125\text{ms}$. Suppose the maximum absolute angular velocity of joint angle during the given kind of rehabilitation training process is $v_{\max}$ (unit: degree per $T_\theta$), and the estimated angular velocity of current time is $v_t = \dot{\theta}_t$, then we can see that: if $|v_t| > v_{\max}$, the estimated angle $\dot{\theta}_t$ is interfered by noise and should be de-noised by AR model above. The final angle estimation results are denoted as $\{\theta_t\}$. The algorithm of AR model–based angle de-noising method is detailed in Fig. 9.

In Fig. 9, $\dot{\theta}_t$ is the joint angle estimated by BP neural network at current time $t$, $\theta_t$ is the final estimated angle and $\theta_{t-i}$ is the final estimated angle at time $(t - T_\theta \times i)$. If $\dot{\theta}_t - \theta_{t-i} > v_{\max}$, $\dot{\theta}_t$ is considered being interfered by noise seriously and should be adjusted: keep the maximum angle variation of $v_{\max}$ and the other part is adjusted by the AR(5) model according to the joint angle variation features; hence, $\theta_t = \sum_{i=1}^5 \varphi_i \theta_{t-i} + v_{\max}$.

If $\dot{\theta}_t - \theta_{t-i} < -v_{\max}$, likewise, $\theta_t = \sum_{i=1}^5 \varphi_i \theta_{t-i} - v_{\max}$.

Else, $\dot{\theta}_t - \theta_{t-i} \leq v_{\max}$, $\dot{\theta}_t$ is considered not being interfered by noise seriously, then $\theta_t = \dot{\theta}_t$.

To conclude, the whole sEMG–joint angle estimation method in this work can be described in Fig. 10.

4. Experiment

To validate the BP–AR-based sEMG–joint angle estimation method proposed in this paper, we have taken some comparison experiments, whose experimental procedure is shown in Fig. 10 and described as follows:

- First, acquiring data samples of three-channel sEMG signals from RF, VL, and SM during cycling exercise, 20s of every subjects ($S_1, S_2, \ldots, S_5$).
- Second, sEMG signal processing procedure. Here two different experiments are taken: one is filtering with Butterworth method after the raw data is sub-sampled by RMS method; and the other one is filtering with moving Butterworth method. The aim is to compare the two filtering methods’ influence on angle estimation accuracy.
- Third, BP neural network–based angle estimation procedure. There are two experiments according to the different signal processing method. Here, two BP neural networks are built for each subject, one uses Butterworth filtered multi-channel sEMG signals as input, and the other uses moving Butterworth filtered signals as inputs. The RMS errors of the experiments by these two BP models are recorded and compared.
- At last, the AR(5)-based angle adjustment procedure is taken to adjust the approximated angles that output by the BP neural network (trained by moving Butterworth filtered signals). Then the angle RMS error, angle velocity RMS errors output by BP model and BP–AR model are recorded and compared.

The experiment results are given in Table 3. In Section 3.1, we know that the moving Butterworth filtering method designed in this work is a time-delay-free filtering method, but the influence on angle estimation accuracy has not been clarified. In the experiment, two BP model with the same structure are built, one used Butterworth filtered multi-channel sEMG signals as input and the angle RMS error results are shown in the first line, while the other uses moving Butterworth filtered signals and the results are shown in the second line. We can see that the results show little difference between each other. Hence, compared with...
### Table 3
Results of Comparison Experiments (Sampling Period = 128 Hz)

<table>
<thead>
<tr>
<th>Methods</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>S4</th>
<th>S5</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Butterworth filtering BP</td>
<td>3.9673</td>
<td>4.3380</td>
<td>4.0780</td>
<td>5.9116</td>
<td>3.3153</td>
<td>4.3220</td>
</tr>
<tr>
<td></td>
<td>Angle RMS error</td>
<td>1.0117</td>
<td>1.3424</td>
<td>1.4522</td>
<td>2.1951</td>
<td>1.3538</td>
</tr>
<tr>
<td></td>
<td>Velocity RMS error</td>
<td>0.7770</td>
<td>0.8871</td>
<td>0.9985</td>
<td>1.0847</td>
<td>0.9467</td>
</tr>
<tr>
<td></td>
<td>Maximum $v_\theta$</td>
<td>2.4968</td>
<td>3.0589</td>
<td>2.9439</td>
<td>3.0892</td>
<td>2.9401</td>
</tr>
</tbody>
</table>

Butterworth filtering method, the moving Butterworth filtering method can not only reduce the time delay, but also have no negative effects on angle estimation accuracy.

The AR model–based de-nosing method aims to optimize the estimated joint angles by adjusting the approximate angles that output by the BP neural network model. Specifically, it can improve the angle estimation accuracy and reduce the singularity points. To validate this method, two experiments were taken using the BP neural network models. First, estimate joint angles $\tilde{y}$ using BP models, get the RMS errors and calculate the angle velocity $v_y$ (degree/$T_\theta$, where $T_\theta = 7.8125$ ms, is the sub-sampling period):

$$v_y = \frac{d\tilde{y}}{dT_\theta} \quad (9)$$

Second, adjust $\tilde{y}$ using AR(5) model–based de-noising method to obtain the final estimated angles $\theta$, then calculate the RMS errors and the angle velocity $v_\theta$:

$$v_\theta = \frac{d\theta}{dT_\theta} \quad (10)$$

$v_y$ and $v_\theta$ series show the continuity of angle $\tilde{y}$ and $\theta$ signals, respectively. As human movements show good continuity, the estimated angles used for rehabilitation training should show good continuity, too.

The results are given in Table 3. We can see that the angle RMS errors in the second experiment are all smaller than the first experiment, hence “BP + AR” method can improve the accuracy stably. Figure 11 shows an example of one set of angle estimation result obtained from the second experiment. The solid line is the sensor detected angle signal, while the dot line is the estimated angles by BP + AR method. Although there are some relatively bigger errors in some area, the results of most parts can approximate the sensor detected angles well.

As to the continuity, the velocity RMS error and maximum angle velocity of $v_\theta$ in the second experiment is much smaller than that of $v_y$. An example of instantaneous angle velocities is shown in Fig. 12. The bold line is the angle velocity of sensor detected angle signal, and we can see the good continuity of human movement through the smooth velocity curve. The dot line is about $v_y$, with maximum of $10.293/T_\theta = 1,317.5^\circ/s$, which will be harmful for patients. We can see that the curve of some parts of $v_y$ vibrates violently making the continuity worse. This is caused by the singularity points, where indicates some estimated angles with locally larger errors, though the mean angle RMS error is small. The fine line is about $v_\theta$, where the amplitudes vibration are much smaller than that of $v_y$. Specifically, compared with $v_y$, the mean of $v_\theta$ is much smaller, and the number of singularity points becomes less. It is proved that the BP–AR method improved the continuity of estimated angles significantly.

The mean RMS error in the experiment of the sEMG–joint angle estimation method proposed in this paper is about $4.27^\circ$, and the mean maximum angle velocity is about $2.90/T_\theta = 371.2^\circ/s$. In addition, the experiment in Section 3.1 shows the moving Butterworth filter can reduce the time delay in signal processing significantly. The summarization time consumption (time delay) of the whole process is about 10–15 ms with PC (Environment: ThinkPad400, Intel Core2 2.26 GHz, 3.0 GB RAM, Windows 7, and MATLAB2009).
Hence, compared with BP method, BP–AR method shows a better performance on angle estimation accuracy and continuity. And also the moving Butterworth filtering method can reduce the time delay significantly.

5. Conclusion and Discussion

For active rehabilitation training exercises, estimating human joint angle by sEMG is one of the most important human motion recognition methods. This paper proposes a BP–AR model-based sEMG–joint angle estimation method to improve the accuracy, continuity and reduce time delay caused by traditional methods.

To validate the proposed method, five able-bodied young subjects participated in the cycling exercises experiment to acquire data samples: seven-channel sEMG signals from lower limb and knee angle. After sub-sampling and feature extraction, the multi-channel sEMG signals were filtered by moving Butterworth filtering method designed in this paper. It can reduce the time delay significantly, and experiment indicated that it can not only flat the original signal well, but also have no negative effects on the angle estimation result. To reduce time consumption, the correlation between every channel of sEMG signal and knee angle signal was analysed, and the signals from rectus femoris (RF), vastus lateralis (VL), soleus muscle (SM) were selected to estimate knee angle.

Then, a BP–AR model-based angle estimation method was proposed. First, a first-order BP neural network was built to map the relationship between three-channel sEMG signal and joint angles. Then, an AR model was built to describe the angle variation features during the given kind of training mode and used to adjust the angles approximated by BP model, so as to get lower angle and velocity RMS errors. The final experiment results showed mean angle RMS error of 4.27° and maximum angle velocity is 371.2°/s with time delay of 10–15 ms (with PC). These final results indicated that, compared with the previous works introduced in Section 1, this method indicated a better performance on real-time computation, accuracy and continuity of sEMG–joint angle estimation.

The BP neural network has been widely used in the field of sEMG–human motion recognition [16]–[18]. Well arranging the structure and transition functions can make the BP network approximate any non-linear function on a compact set. This work used a three-layer BP network to build the non-linear relationship between three-channel sEMG signals and knee angles. In applications, the recorded sEMG signal is interfered with some random noises that are very difficult to be removed even the signal is filtered. Some intensive interference may occur at some time points and then make relative bigger local errors of the estimated joint angles. These locally bigger errors have little effects on the mean RMS error, as they are in small numbers; but they can make the continuity of estimated joint angles worse. The control effect of rehabilitation machine relays on not only the angle estimation accuracy but also the continuity. Hence, reducing both the mean error and the locally bigger error is important. Increase of the amount of order and hidden layer nodes of BP neural network can improve the approximation accuracy, however, needs more time and space to complete the work. When the increments of order and hidden layer’s nodes go to a certain extent, the improvement of angle approximation accuracy will be nowhere near as beneficial as the increment of time and space consumption.

Therefore, to improve the accuracy, continuity and time consumption, we can use a BP network with a relatively simple structure to map the relationship of multi-channel sEMG signals and knee angles, so as to make the mean error in an acceptable range according to control requirement; and then use another simple and practical way to reduce the locally bigger errors. The joint angle variation features of some limb rehabilitation modes are simpler and linear-like; the angle of current time depends very much on the angles of previous in time sequence. For example, the knee angle variation feature of cycling exercise is like sine wave. The AR model is a special case of time series that specifies that the output variable depends linearly on its own previous values. It can model the linear relationship, and both its training and calculation are much simpler than BP neural network [29]. The experiments showed that just AR model with low order can describe the joint angle variation features of given rehabilitation motion pattern and so can be used to reduce the locally bigger errors of angle estimation results by adjusting the BP estimated angles. That is the reason of combining BP and AR model together in this work. BP–AR model can utilize both the advantages of BP neural network and AR model. Compared to BP method, BP–AR method can improve the angle estimation accuracy, continuity and reduce time consumption at the same time.

This paper used the data samples from healthy bodies to study the relationship between multi-channel sEMG and joint angle. However, the sEMG signals from stroke patients are weaker because of the injury of their motion neuromuscular system. Therefore, the patients should be categorized according their conditions in application, and large samples should be acquired to train different models respectively. Then the estimated joint angles can be used as references for control information of the active rehabilitation system [30].

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