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Continuous estimation of joint angle from electromyography using multiple time-delayed features and random forests

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ABSTRACT

To estimate the continuous human motion from surface electromyography (sEMG), it is required to extract hidden information from sEMG and generalize an estimation model. In this study, we proposed that the multiple time-delayed feature (MTDF) signals of sEMG improve the performance of elbow joint motion estimation. Among different learning algorithms, we found Random Forests (RF) to be the best in terms of execution time and accuracy of estimation. Features of sEMG that were best describing the joint motion included: mean absolute value, waveform length, zero crossing, slope signs changes, and difference absolute standard deviation value. The speed of joint movement ranged from 15°/s to 180°/s. The time-delay coefficient and the optimal time-delayed coefficient of RF using MTDF method were 2 and 317, respectively. Mean difference and the standard difference between the actual angle and the estimated angle, using the Bland-Altman analysis, were 0.08 and 5.01, respectively. The average root mean square difference value was 0.0543 ± 0.0071. In addition, the average execution time of motion estimation of a 17.57-s signal was 0.2642 seconds. We found the RF algorithm using MTDF features as the most robust method to estimate the elbow joint motion.

1. Introduction

Surface electromyography (sEMG) is a non-invasive biological signal reflecting human's voluntary motion, and it has been successfully applied as the control signal of the exoskeleton robot to realize a friendly human-robot interface [1–4]. Recently, researchers proposed some pattern recognition algorithms to estimate the human motion from sEMG [5–7]. However, the performance of human motion recognition by using the pattern recognition method is still limited. The human motion is continuous, but the pattern recognition method could only be applied to recognize the discrete motion. Therefore, it is hard to be used to achieve the continuous motion estimation. In the course of recognizing continuous human motion from sEMG, two key steps are involved: 1) extracting the feature signals from sEMG and 2) estimating the continuous human motion from the feature signals of sEMG.

The raw sEMG signal is extremely weak and its energy mainly distributes on the frequency range of $(13 \sim 500)Hz$ [1–4]. Generally, the time-domain feature signals of sEMG such as mean absolute value (MAV), waveform length (WL), and zero crossing (ZC) are extracted to represent the role of sEMG in the course of motion estimation. The time-domain feature signals are calculated directly from sEMG, and they can be obtained with the sliding window function [8–11]. WL, MAV and difference absolute standard deviation value (DASDV) are common feature signals of sEMG for the estimation of human movement [12–14]. WL describes the complexity of sEMG signal [12]. MAV is an average of absolute value of the sEMG signal amplitude in segment [13]. DASDV represents the standard deviation value of the wavelength of the sEMG signal and it is an important power index of sEMG [14]. ZC and SSC describing the frequency information of the sEMG signal are two important features defined in the time-domain [12].

The joint angle is an essential indicator to describe the human motion, and the problem of joint angle estimation from sEMG attracts many researchers. Some methods based on the Hill muscular model, artificial neural network, support vector machine (SVM)

Abbreviations: sEMG, surface electromyography; RF, random forests; MTDF, multiple time-delayed features; MAV, mean absolute value; WL, waveform length; ZC, zero crossing; SSC, slope signs changes; DASDV, difference absolute standard deviation value; RBF, radial basis function; BP, back propagation; SVM, support vector machine; TDANN, time-delayed artificial neural network; RMSD, root mean square difference.

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and so on were proposed in [15–20]. In [15], [16], the Hill muscular model was applied to establish the biomechanical model to describe the relationship between sEMG and the joint angle. However, many parameters of these biomechanical models had to be determined and the performance of motion estimation by using these models were not well. The human limbs are irregular and flexible, therefore, the biomechanical model will be insufficient and it is hard to be applied to describe the characteristics of human limbs very well. Furthermore, some unknown factors which may be applied to improve the accuracy of biomechanical models are still to be explored. Therefore, some researchers considered to replace the biomechanical models with the universal models based on the machine learning technology such as radial basis function (RBF) neural network, back propagation (BP) neural network, and SVM [17–21]. In [17], Yang Chen et al. proposed a hierarchical projected regression method to estimate the joint angle of human elbow online. Lizhi Pan et al. established a state-space model with unknown structure to be applied to estimate the finger joint angle [18], and some time-domain feature signals of sEMG (MAV, ZC, WL, and SSC) were extracted to represent the role of sEMG. Shengxin Wang et al. [19] applied the RBF neural network to estimate the tremor joint angle from root mean square of sEMG. Zhichuan Tang et al. [20] used the BP neural network to map the nonlinear relationship between sEMG and the elbow joint angle. However, the performance of motion estimation in these papers were still not well. The reason is that one single feature signal of sEMG used in [19], [20] or the multiple feature signals used in [17], [18] could not reflect the actual motion information very well. In other words, the feature signals used in these papers are still not enough to represent the role of sEMG very well in the course of motion estimation.

The time-delayed signals of sEMG was applied in the course of motion estimation from sEMG by Arthur T.C. Au et al. in [21]. In [21], Arthur T.C. Au et al. presented a time-delayed artificial neural network (TDANN) to estimate the shoulder and elbow motions. In addition, they used the low-pass filtering sEMG signal with 4 *Hz* and its time-delayed signal to estimate the joint motion. In [22], Hadi Kalani et al. used the TDANN to estimate the rhythmic clenching movements from sEMG. Meanwhile, the sEMG signals were rectified and smoothed by a moving average window. In these two papers, only the low-pass filtering sEMG signal and its time-delayed signal were extracted from sEMG. Compared with the traditional feature signals listed in [23], the low-pass filtering sEMG signal may lose much useful information. Inspired by these works, we intended to explore if some important information of motion were also hidden in the time-delayed signals of the traditional feature of sEMG such as MAV, WL, and SSC. However, one single feature signal was insufficient. In this work, we considered to apply multiple feature signals and their time-delayed signals to improve the estimation accuracy in the course of motion estimation. However, the multiple feature signals of sEMG and their time-delayed signals formed a high dimensional data set which would increase the execution time in the course of motion estimation [24]. Therefore, the execution time should be decreased.

To solve these problems, the RF algorithm being suitable to be used to solve the high dimensional data problem [25] was applied in this work. Compared with artificial neural network and SVM, its advantages over them can be summarized as: fast execution time, avoiding over fitting and powerful in resistance to noise [24], [26]. The execution time of RF is far less than RBF and SVM when they are used to process high dimensional data [24], [26]. What is more, the mean decrease in accuracy method of RF can be applied to describe the importance of features. To our knowledge, no researchers have ever considered to apply the RF algorithm to estimate the continuous human motion from sEMG. The RF algorithm proposed by Leo Breiman is a combination of tree predictors [26]. It is a very efficient algorithm and has been applied in many aspects, such as risk estimation [27], population density estimation [28], and variable selection [29]. In [30], the RF algorithm was used for EMG patterns classification. In [31], Fraiwan, Luay et al. applied the RF to recognize the voiceless Arabic vowels from the facial EMG signal.

The aim of this study is to verify that the multiple time-delayed feature signals of sEMG could be applied to improve the performance of motion estimation. To decrease the execution time in the course of motion estimation and improve the performance of motion estimation, the RF algorithm was applied to establish the regression relationship between MTDF and the joint angle. In this work, the flexion and extension of human elbow joint were estimated from sEMG signals of the biceps brachii and the triceps brachii muscles. Considering the computational complexity, five main features of sEMG were used in this work, namely, MAV, WL, ZC, SSC and DASDV. BP neural network, RBF neural network and SVM were also applied to verify the significance of time-delayed feature signals of sEMG in the course of motion estimation. The experimental results showed that the multiple time-delayed feature signals indeed played vital role in the course of estimation, and the RF algorithm using MTDF method could be used to estimate the joint motion with the best performance.

Table 1
The information of subjects.

Subject	Sex	Age
A	male	26
B	male	28
C	female	24
D	male	49
E	female	31
F	male	29
G	female	32
H	female	42
I	male	34

2. Methods

2.1. Experimental paradigm

In this study, nine healthy subjects (five males, four females, 24 ∼ 49 years old) without any history of neuromuscular disorder were selected. All subjects were represented with capital letters and the information of these subjects were listed in Table 1. Before the test, all subjects were introduced the experimental protocol and given the informed consents.

In the course of experiments, the wrist of experimental subject was kept along with the forearm to ensure that only one degree of freedom elbow joint motion in the vertical plane existed. Meanwhile, the upper arm and the forearm should keep relaxed to avoid that the muscular tone may introduce offset into the signals. Each subject repeated the experiment ten times and had a rest of three minutes between two adjacent experiments avoiding muscle fatigue. According to [32], the range of elbow joint motion is $40^\circ \sim 180^\circ$. As a result, the range of angle in experiments was set as $40^\circ \sim 180^\circ$.

2.2. Experimental setup and data acquisition

The experimental set-up is shown in Fig. 1. The flexion and extension of elbow joint are taken as an example in this work. The flexion of elbow joint is mainly associated with the biceps brachii, the brachialis, and the brachioradialis. Meanwhile, the extension is mainly related with the triceps brachii muscles and the anconeus [33–37]. Considering the computational complexity, the biceps brachii and the triceps brachii were taken as the main