sEMG-based Hand Gesture Classification with Transient Signal

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Abstract. Surface electromyography (sEMG) can provide a novel control method for human machine interface (HMI) with the improvement of signal decoding technology. sEMG-based hand gesture recognition is the key part of HMI control strategy. However, unstable and complex daily used scenarios hinder the further development of sEMG-based control strategy. In this paper, we concentrate on the data preprocessing part. Three different signal segments were extracted including the transient signal segments between gestures, standard signal segments and stationary signal segments which is smaller than standard segment. By setting up several experiments to analyze and evaluate the classification performance with these transient information. Our research found that transient signal segments can reflects more effective information than the stationary signals in inter-subject scenes. It gained more classification accuracy and stability. In addition, it also performance better in other two scenes in ten hand gesture recognition in intra-session and inter-session.

Keywords: sEMG, Feature extraction, traditional classifier, transient signal

1 Introduction

Surface electromyography is a bioelectrical signal that represents the impulses of motor units during skeletal muscle fiber excitement and contraction. It is a comprehensive temporal and spatial characteristic map of electrical activity of complex subepidermal muscles, which can be extracted from the surface of the skin by recorded electrodes. There are different degrees of correlation between sEMG signals and muscle activity and function, which reflects neuromuscular activity to a certain extent(see [1]).

Given the characteristic that sEMG signals are easy to collect, non-invasive, and bionic, many researchers have devoted themselves to studying the essential characteristics of sEMG signals, revealing the physiological mechanism that they generate and the muscle motor systems they reflect. At present, sEMG is widely used in the diagnosis and rehabilitation of neuromuscular diseases including muscle physiology, muscle metabolism, rehabilitation medicine, sports and other fields(see [2]). In addition, sEMG can also be used to provide a safe, non-intrusive control method for advanced prosthesis control, functional electrical stimulation and other advanced HMI(see [3] and [4]). The sEMG-based gesture recognition studied in this paper is a key part of the control of multifunctional dexterous prosthetic hand. Also, it is an important research direction in the field of rehabilitation and intelligent control.

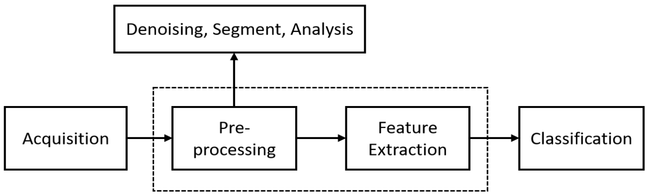

Fig. 1. Signal processing flow

Currently, gesture recognition based on pattern recognition has been regarded as the optimizing approach among different kind of strategies(see [5]). A general pattern recognition system can be divided into four parts: data collection, data preprocessing, feature extraction and classification, as shown in figure 1. Each part has a significant impact on the results of gesture recognition. In data collection, we always use an advanced commercial equipment to extract weak effective signals. Data preprocessing is always combined with the part of feature extraction(see [6]), it plays a vital role in feature extraction. The raw signal from acquisition device is often accompanied by some unstable noise which hinder the classification performance. Data preprocessing can remove the noise by some software filtering methods, such as high-pass filtering or low-pass filtering. In addition, this part can also extract and segment the needed part of signal. Feature extraction plays a critical role to the classification performance(see [7] and [8] and [9]). It obtains the characteristic parameters of each analysis window to characterize the characteristic vector of the EMG signal. So far, a large number of sEMG features have been investigated for hand gesture classification, and they can be summarized into four types: time domain (TD), frequency domain (FD), time-frequency domain (TFD) and parametric model analysis. Phinyomark et al.(see [10]) compared thirty-seven TD features and FD features, the experimental result demonstrated that the top three sEMG features could reach the accuracy more than 80 %. Besides that, it reveals that most of the TD features were redundant and better than the FD features. Classification is used to build a model which can map the characteristic vector to different motions. Generally, some classic supervised classification methods are used in gesture recognition, such as linear discriminant analysis (LDA), support vector machine (SVM), Naive Bayes and K nearest neighbor (KNN).

Although myoelectric pattern recognition approach can achieve good performance in special laboratory environment, but failed in daily life due to the changes between training data and testing data generated by muscle fatigue(see [7]), electrode shifts(see [8]), and arm position changes(see [9]). To overcome the influence of these external factors, some methods were proposed. Deep learning (DL) has become popular in recent years and has achieved outstanding performance in many fields, such as image processing, speech recognition and natural language processing(see [11]). Convolutional neural network (CNN) and recurrent neural network (RNN), two classic network architectures of deep learning, have been applied to the gesture classification of sEMG. Manfredo et al.(see [12]) use a simple CNN architecture which is combined by four convolutional layers, one fully connected layer and a softmax function to classify the gestures on DB1 in Ninapro database. Finally, it obtains 4.53% higher accuracy than the classical classification methods. Geng et al.(see [13]) applied a deep CNN to a high-density EMG, and achieved an accuracy of 89.3% with a single frame and 99.0% with over 40 frames for 8 gestures recognition. Adaptive learning can enhance the robust of algorithm by adjusting the parameters of training model when external factors changes. Liu J.(see [14]) proposed an adaptive unsupervised classifier based on support vector machine and incremental learning method. This classifier considers the real-time changes between testing data and training data when predict the classification label. Then some adjustments on these difference would be added to the classification model in an unsupervised manner. Thus, continuously updating the model parameters makes the classifier adaptive to the changes. Chen et al.(see [15]) extend two off-line pattern recognition methods, linear discriminant analysis and quadratic discriminant analysis, to self-enhancing methods which continuously updating the class mean vectors, the class covariance and the pooled covariance using the testing data respectively.

In general, researchers always place their focus point on feature extraction and classification. They regard the signal of stationary section of a gesture as the most representative data. However, when capturing sEMG data of a repeated gesture in different session, the experimental volunteer completes the motion with different force because of fatigue or force information missing. Thus, the different session of stationary section exists some unstable factors. In this paper, we will extract transient signal segments when a hand gesture changes as the input data. Several TD features and supervised classifications will be used to compare with traditional processes.

2 Material and methods

2.1 Subjects

Eight able-bodied subjects are employed in to investigate the classification performance with the transient signal segments of sEMG signals. (1 female, 7 males, age: 25±5,height: 175±10cm, weight: 65±10kg). Subjects have no previous history of neuropathies or traumas to the upper limbs and fingers. They were obtained full informed consent according to the Declaration of Helsinki. All subjects receive the relevant guidelines before capturing sEMG data during the entire experiment. The data capture cycle was one week.

2.2 Apparatus

Fig. 2. The electrode sleeve for sEMG signal recording, 16 monopolar channels record the differential voltage between electrode 1-16 and electrode 17 and 18 provides the bias voltage to remove DC offset.

To capture the sEMG signal on the forearm, a multi-channel sEMG acquisition system, developed by our research group(see [16]), was employed to record the multi-channel sEMG signals. This device supports up to 16 bipolar EMG channels, 5000 amplification gains, 1kHz sampling frequency and 12 bits ADC resolution. To remove the motion artefacts, a band-pass filter with cutoff frequencies at 20Hz and 500Hz is integrated in the device. In addition, a notch filter with the fundamental frequency at 50Hz is also deployed in hardware to remove the power frequency signal from the power line. The noise of each EMG channel was less than 1V. The entire device was powered by a 3.3V rechargeable lithium battery, supporting continuous signal recording for up to ten hours.

This acquisition system use an electrode sleeve as signal conducting and recording equipment, as seen fig. 2, which embedded 18 electrodes in Zig configuration on an elastic fabric sleeve(see [17]). The diameter of each electrode is 12 mm, 25 mm vertical and 30 mm vertical and horizontal distances between two electrodes. 1 to 16 represent 16 independent channels, one reference electrode marked as 17 and one bias electrode marked as 18. All 16 channels are recorded synchronously.

2.3 Acquisition Protocol

Before the experiment, each subject should wear the electrode sleeve in the right way. They were required to be familiar with the experimental process and

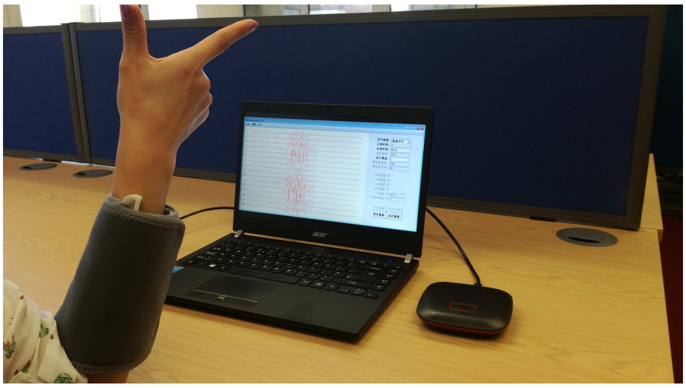

Fig. 3. The scenes for sEMG data recording.

practice the pre-defined hand gestures for several minutes. The selected of hand gestures in this experiment refer to the NinaPro dataset(see [18]) and CSL-HDEMG database(see [19]) which are the two popular sEMG databases. All the hand gestures can be seen in fig. 4. Among them, the first row contains five finger-related gestures, they are (1) tip pinch, (2) flexion of ring and little finger, thumb flexed over ring and little finger, (3) flexion of middle, (4) ring and little finger, middle and ring flexion, and (5) thump up. The second row is wrist-related gestures, includes (1) hand close, (2) hand open, (3) wrist deviation, (4) wrist extension and (5) wrist flexion. Each subject was asked to complete the action with norm strength.

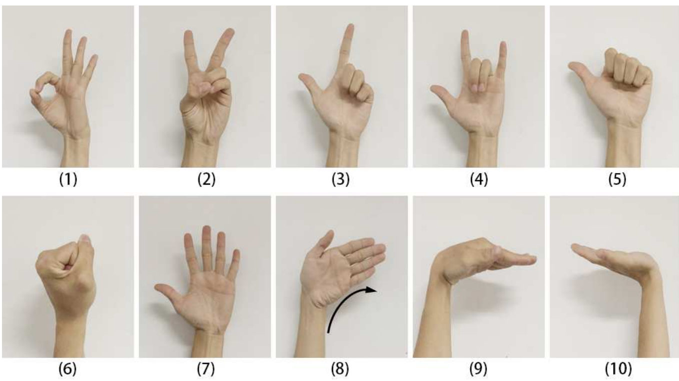

Fig. 4. Ten gestures were used for this experiment. (1)tip pinch, (2)flexion of ring and little finger, thumb flexed over ring and little finger, (3)flexion of middle, (4)ring and little finger, middle and ring flexion, and (5)thump up, (6)hand close (hc),(7)hand open (ho), (8)wrist radial deviation (wrd), (9)wrist extension (we), (10)wrist flexion (wf).

Throughout the acquisition process, each subject wore the electrode sleeve on the left forearm and keep a standard sitting position in comfortable on the chair, as seen in fig. 2. Ten hand gestures were performed in sequence and each gesture maintained for at least 12s. In order to avoid muscle fatigue, subjects were asked to relax their hand for at least 10s between two adjacent gestures in a session. After finishing the ten hand gestures collected in short period, the subjects were asked to have a rest for half an hour. In this time period, subject can move around the office without removing the sleeve. The second session and third session were carried out in the same way. So, we separately gained three sessions from each subject and all sessions have the same electrode distribution. After three days, another three sessions were carried out to collect sEMG signals from each subject in the same way. It was worth pointing out that no predefined contraction force or elbow angle were applied in the experiment to mimic the real application of a sEMG based HMI as much as possible, although it was well known that muscular contract force and arm position could influence the robustness of patter recognition system (see [20]).

2.4 Data Preprocessing

Table 1. The format of EMG database.

aaa-ccc.mat

Name	Type	Description
subject	scalar	The subject ID
group	scalar	Gesture group ID
data	110000×16 matrix	Raw sEMG signals of five gestures

ss-aaa-bbb-ccc.mat

Name	Type	Description
shape	scalar	The segmented shape ID
subject	scalar	The subject ID
gesture	scalar	The gesture ID
trial	scalar	The trail ID
data	10000×16 matrix	sEMG data for standard
	4000×16 matrix	sEMG data for one transient
	6000×16 matrix	sEMG data for one stationary

According to the acquisition protocol, each session contains ten hand gestures and each gesture maintained for 12s. To evaluate the performance of transient segments of sEMG signals in classification, we segment the raw data into three shapes: standard signal segments, transient signal segments, stationary signal segments. First, we extract standard section part. Only the later 10s of 12s signals of each gesture were segmented and labeled for classification. It was to exclude the transient state between two gestures. Thus, 10s stationary sEMG signal containing 10000 frames were extracted for further processing and analysis. Then, the stationary section has the same segmented methods except the effective segmentation area is in the middle of standard section. Only 12s to 18s signals of each gesture were segmented and labeled for classification. At last, transient segment part was processed. There is a movement process when the gesture changes from a rest state to a specific action and this process will hold for 1s or 2s in the earlier part of 12s signals. To collected enough transient information during the changes between gestures, We defined the earlier 4s of 12s signals as the transient segment. Only 8s to 12s signals of each gesture were segmented for training and testing.

The whole dataset was organized in Matlab format with architecture as described in Table I. The files titled in the format of aaa-ccc.mat and ss-aaa-bbb-ccc.mat indicated the raw and preprocessing data, respectively, where aaa was the subject ID, BBB was the gesture ID, ccc was the session ID and ss represent the three segmented shapes: standard, transient and stationary. For example, 001-002.mat represent the raw sEMG data captured from subject 1 in the second session, and 02-003-004-005.mat contained the transient sEMG data of gesture 4, captured from subject 3 in the fifth session.

2.5 Feature Extraction and Classification

TD features outperformed most feature extraction methods. Moreover, it is low calculation. In this paper, we choose four TD features and an AR model with four coefficients as the evaluation features. In this scheme, each analysis window is equal to 300 ms (300 samples in 1kHz sampling) and each incremental window is set to 100 ms. The selected four TD features are: Modified mean absolute value (MAV), Waveform length (WL), Root Mean Square(RMS) and Average amplitude change (AAC) .

For the classification of the sEMG signals, three traditional classification methods were implemented in MATLAB tool: SVM, LDA and KNN. Initially, the SVM classification with Radial Basis Function (RBF) kernel were applied and the gamma of kernel function is set to 0.125.

3 Experiment setup

To verify the classification with transient signal segments can acquire similar or superior performance than the other two, three types of experiment and evaluation method as listed below.

Table 2. a comparison of three segmented shapes with different classification algorithms in inter-session evaluation.

Method	transient			stationary			standard		
	KNN	LDA	SVM	KNN	LDA	SVM	KNN	LDA	SVM
WL	0.7060	0.6698	0.6585	0.6935	0.6882	0.7220	**0.6935**	0.6882	0.7224
RMS	0.6921	0.6771	0.6621	0.6826	0.7075	0.7298	0.6900	0.6942	0.7213
MAV	**0.7132**	0.6985	0.6258	**0.6991**	0.7103	0.6504	0.6689	0.7116	0.6962
AR4	0.6744	**0.7895**	**0.7732**	0.6391	**0.8238**	**0.7943**	0.6528	**0.8252**	**0.8074**
AAC	0.6768	0.6875	0.6620	0.6623	0.7164	0.7097	0.6706	0.6953	0.7295

[1] Abbreviations: Waveform length(WL), Root mean square(RMS), Modified mean absolute value(MAV), Auto-regressive coefficients(AR4), Average amplitude change(AAC).

Table 3. a comparison of three segmented shapes with different classification algorithms in inter-subject evaluation.

Method	transient			stationary			standard		
	KNN	LDA	SVM	KNN	LDA	SVM	KNN	LDA	SVM
WL	0.5743	0.5635	0.5554	0.5397	0.5175	0.5774	0.5406	0.5311	0.5565
RMS	0.6143	0.5413	0.5946	0.5362	0.5150	0.5746	0.5486	0.5246	0.4981
MAV	**0.5983**	0.5494	0.5524	**0.5465**	0.5163	0.5812	**0.5558**	0.5245	0.5185
AR4	0.4865	0.5612	0.6211	0.4751	**0.5621**	**0.5958**	0.4808	**0.5645**	**0.5823**
AAC	0.5742	**0.6636**	**0.6358**	0.5396	0.5175	0.5689	0.5389	0.5311	0.5102

3.1 Intra-session strategy

To evaluate the general classification performance, data within one session was used in this experiment. All subjects are independent, so we choose one subjects data to repeat the procedure. Each session will be divided into training data and testing data. The average classification accuracy across six tests was used to evaluate the performance of the three segmented shapes.

3.2 Inter-session strategy

Three sessions collected in the same electrode distribution were used for training and the remaining three sessions collected in three days later for testing. Then, the later three sessions for training and earlier three sessions for testing. Although the training and testing data were collected from the same subject, a large gap will exist between them due to electrode shift, etc. The average classification accuracy across eight tests was used to evaluate the performance of the three segmented shapes.

3.3 Inter-subject strategy

A single subjects data was chosen to testing the classifier and the remaining data as the training dataset. In the current case, eight training and testing procedures will be executed, the data of one of eight subjects were used as the testing data in turn, and the remaining data as the training data. The average classification accuracy across eight tests was used to evaluate the performance of the three segmented shapes.

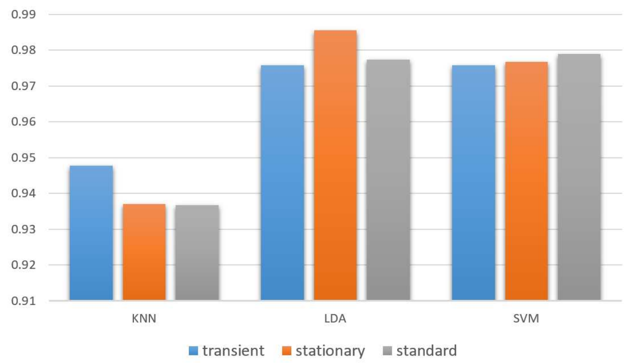

Fig. 5. The classification accuracy between three segemented shapes.

4 Results and Discussion

4.1 classification accuracy performance

Three different experiments were implemented in this paper to evaluate the performance of different preprocessing methods. In the intra-session part, a combination of feature extraction and classification methods were applied to the three segmented shapes. The result can be summarized as a histogram in the fig. 5. The average accuracy is over 90%. LDA can gained more accuracy compared to two other classifications. The transient signal segments between two gestures hidden some important information of muscle contraction.

In the part of inter-session, the experimental results demonstrated that the classification with transient signal segments are similar to the other two, as listed in TABLE II, the highest accuracy that transient segments acquired is 78.95% with the LDA and AR4. In addition, LDA outperformed the other two classifier in three segmented shapes, it obtains the highest 78.95%, 82.38% and 82.52%, respectively, in the three shapes. AR4 can achieve better characterization of feature vector and get better classification performance with different classifier.

As seen in TABLE III, the classification accuracy of inter-subject can be seen in the table. The accuracy of transient signal segment performed best. It acquired 66.36% with LDA and AAC, which is 6% higher than the top accuracy in stationary signal segment and standard signal segment. Besides, the average accuracy of transient is around 55% to 60%, which illustrate the stability of transient signal segment in inter-subject. Among all the features, AR4 and AAC performed better.

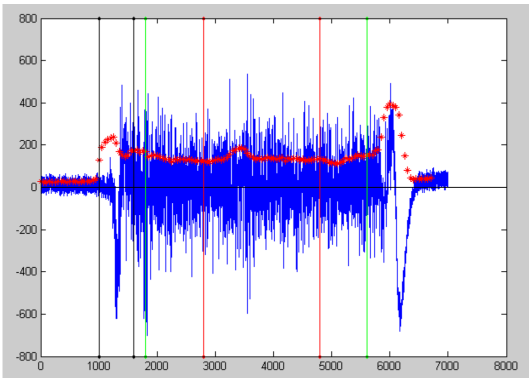

Fig. 6. The three segmented shapes in raw and feature data plot.

4.2 discussion

As we can see in the fig. 6, raw data signals of one gesture was plotted on the figure, blue curve represent the raw signal, the red dotted line represent the RMS feature extracted from this signal with the length of analysis window is 100, and shift window is 50. In general, we extract the effective signal between green line, which is standard and steady. Sometimes, real-time performance is required, so signal segment between red lines will be extract as the whole representative of the motion. The signal segment between two black lines in the left is the transient signal which occurs along with hand gestures changes.

In intra-session, the sEMG data is offline, any popular machine learning classifier can extract the hidden model between the training data and theirs labels. However, when external environment changes, model extracted from the stationary signal segments will be expired. Compared to the stationary signal, Transient signal is always related to the changes, which decrease the influences by external factors. Certainly, the classification accuracy with transient signal segments is not very well for daily use, some essential characteristics should be discoverd.

5 Conclusion

In this paper, we discuss the transient signal segments acquired when gesture changes. To reveal the useful information hidden in the transient signal, we designed some comparative experiments. Three kinds of signal segments were extracted as the representative sector of hand gestures. Traditional feature extraction methods including WL, AAC, AR4, RMS, MAV and classification methods are combined to evaluate the proposed methods. The results show that transient signal segments can achieve satisfactory result in single session. In addition, transient signal segments can gain more stable representative information between different subjects. It acquired better classification performance in the part of inter-subject. Two referenced segmented shapes, stationary and standard, are all extracted from the steady part of one hand gesture, they can get almost the same performance in three experiments, which illustrate that some representative small stationary signal segment can get better performance in accuracy and calculation cost. In the future, we plan to fit the transient sectors by some regression methods for promoting the robustness of long-term sEMG signals.

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