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A New Feature Extraction Method Based on Autoregressive Power Spectrum for Improving sEMG Classification*

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***Abstract*— The feature extraction is an important step to achieve multifunctional prosthetic control based on surface electromyography (sEMG) pattern recognition. In this study, we propose a new sEMG feature extraction method which is based on autoregressive power spectrum (ARPS). An experiment with a task containing thirteen motion classes was developed to examine the effectiveness of this method. The results show that the new feature, ARPS, has better performance comparing with other two frequently used features, the time domain set (TDS) and autoregressive coefficients (ARC). The ARPS obtains the highest separability index (SI)—a metric measuring the discriminative ability of the sEMG feature. And the average classification errors of ARPS, TDS and ARC are 5.00%, 8.43% and 6.39% respectively. This suggests that the ARPS is suitable for the sEMG pattern recognition.**

I. INTRODUCTION

The surface electromyography (sEMG) signal is the electric potential measured on the skin surface of a muscle. It contains the control information from central nervous system (CNS) and can be used to control electrical powered prostheses [1].

Recently, a large number of studies describing sEMG pattern recognition have been carried out to achieve the multifunctional prosthetic control. Fig. 1 illustrates the basic process of sEMG pattern recognition. During a user performs a motion contraction, the preprocessed sEMG signals (amplified, filtered and sampled) are firstly collected into window data with appropriate length. Then, some sEMG features are extracted from these window data by kinds of signal processing methods. These features are fed into the classifier which has been trained off-line. Finally the classifier recognises which motion is executed by the user to control the movement of prosthesis.

As we can see in Fig. 1, feature extraction is one of most important procedures to obtain high sEMG pattern recognition rate. Therefore many researches have been developed to extract useful features for representation of the sEMG signals, such as time domain features [2], time-frequency representation [3] and high order statistics [4]. Autoregressive (AR) model analysis was first used in [5], [6] to fit sEMG signal for identifying different limb functions.

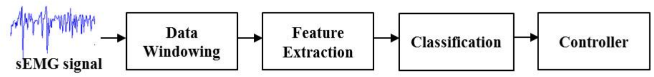

Fig. 1. Schematic blocks of myoelectric control based on pattern recognition.

Afterwards, many studies have adopted the AR coefficients as the sEMG feature and proved the effectiveness [7], [8], [9]. Furthermore, the power spectrum also has been used to represent the sEMG signal [10]. Generally, previous studies estimated the power spectrum based on discrete Fourier transform and used the median frequency (MDF) or mean frequency (MNF) as the sEMG feature. However, the performances of these two features were weak [11].

In this study, a new sEMG feature extraction method based on autoregressive power spectrum is proposed. Contrast to the AR coefficients are used as the sEMG feature as in [7], [8], we use the AR coefficients to estimate the power spectrum of the sEMG signals. After that, the logarithmic transformation is applied on the spectrum and only a subband of the spectrum is used to suppress the effect of noise. The usable band is segmented and each segment is averaged. We verify the hypothesis that the segmented averages can extract more information about the spectrum of the sEMG signal, comparing with the MDF and MNF.

The experiment containing thirteen wrist or hand motion classes was carried out to validate this assumption. The result shows that this new kind of feature has an excellent capability to represent the sEMG signals of different motions and can improve the sEMG classification.

II. METHODS

A. Declaration

All recruited subjects had signed the informed consents before experiment. The procedures conformed to the Declaration of Helsinki.

B. Experiment Protocol

Five healthy males with intact arm participated in this experiment. The Trigno Wireless System (DELSYS INC, USA) was used to record the surface myoelectric signals. Four wireless EMG sensors were placed on four forearm muscles, namely, extensor carpi ulnaris, flexor carpi ulnaris, extensor carpi radias and extensor digitorum, which were found by palpation when the participant was instructed

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to perform hand motions. The sEMG signals were bandpass filtered (20–450 Hz) and sampled at 2000 Hz by the collecting system.

Before the experiment, the forearm skin was rubbed with alcohol to provide good condition of sEMG signal acquisition. The participant was instructed to naturally hang his arm at side. The sEMG signals of twelve contraction classes plus the rest class would be collected in the experiment. These contraction classes are fist, open hand, wrist flexion, wrist extension, radial deviation, ulnar deviation, pronation, supination, fine pinch, key grip, ball grasp and cylinder grasp as showed in Fig. 2. In each trial, the participant performed one of the thirteen classes for 5 seconds with a 5 seconds break between two adjacent classes. After each trial the participant was given some minutes for relax. Totally 20 trials data were collected for each participant.

Fig. 2. Twelve contraction classes. From left to right and up to down these are wrist flexion, wrist extension, radial deviation, ulnar deviation, pronation, supination, fist, open hand, fine pinch, key grip, ball grasp and cylinder grasp. Note that the rest class is not showed here.

C. Data Preprocessing

Only the centeral 4 seconds part of each 5 seconds contraction data are used for analysis in order to remove the transient state of the contraction. The data are segmented into a series of 200ms windows with 50% overlap and the sEMG features are extracted from each of these windows.

D. Feature Extraction

In this section, we introduce the sEMG feature extraction method depending on autoregressive power spectrum. First, the autoregressive power spectrum [12] of the windowed sEMG signals can be computed as

$$s(n) = \sum_{k=1}^{p} a_k s(n-k) + e(n) \tag{1}$$

$$\hat{P}_{AR}(e^{j\omega}) = \frac{\hat{\rho}_e}{|1+\sum_{k=1}^{p} a_k e^{-j\omega k}|^2} \tag{2}$$

Equation (1) defines the sEMG signals $s(n)$ as a p order AR model. a_i is the ith AR coefficient and the innovation $e(n)$ is regarded as the Gaussian white noise. Equation (2) computes the autoregressive power spectrum depending on the model constructed in (1). Where $\hat{\rho}_e$ is the power estimation of $e(n)$.

After the autoregressive power spectrum is computed, the logarithmic transformation is applied on it to make it more smooth and suppress the effect of noise. Only the spectrum of 20-450 Hz (note that he signals have been bandpass filtered by hardware in 20-450 Hz) is used to eliminate the motion artifacts and the high frequency noise. And then the spectrum (20-450 Hz) is divided into N frequency bins and the components in each bin are averaged. Therefore we obtain a N dimensional feature vector from one channel of the windowed sEMG signals. Fig. 3 shows the autoregressive power spectrum of the sEMG signals and the logarithmic transformation of it.

The order p is chosen as six [7] and the number of bins N is chosen as ten. Therefore a 40 ($4 \times 10 = 40$) dimensional feature vector for each frame of sEMG signals is obtained. We denote this new kind of sEMG feature based on autoregressive power spectrum as ARPS. We compare this new kind of feature with other two frequently used features to prove the effectiveness of the method proposed.

- The time domain feature set [13] contains mean absolute value, waveform length, zero crossing and slope sign changes (dimension of the feature vector is 16, $4 \times 4 = 16$ and is denoted as TDS).
- The autoregressive coefficients. The order p is equal to ARPS (dimension of the feature vector is 24, $4 \times 6 = 24$ and is denoted as ARC).

E. Performance Evaluation

1) Separability Index: Before classification, some criteria can be used to quantitatively measure the separability of the sEMG features [14]. The Bhattacharyya distance (BD) [15] providing the upper and lower bounds of the Bayes classification error is adopted to define the separability index (SI) as

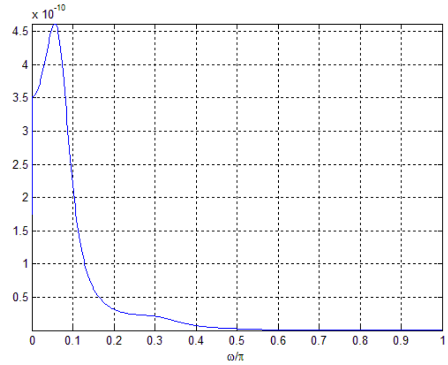
$$SI = \frac{2}{C(C-1)} \sum_{i=1}^{C-1} \sum_{j=i+1}^{C} BD_{ij} \tag{3}$$

and

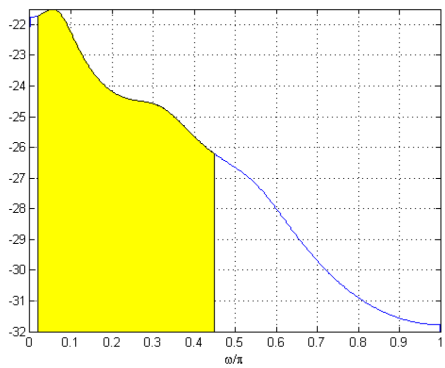
$$BD_{ij} = \frac{1}{8}(\mu_i - \mu_j)^T (\frac{\Sigma_i + \Sigma_j}{2})^{-1} (\mu_i - \mu_j) + \frac{1}{2} \ln \frac{|\frac{\Sigma_i + \Sigma_j}{2}|}{\sqrt{|\Sigma_i||\Sigma_j|}} \tag{4}$$

where C is the number of motion classes, μ_i and μ_j are the centroid of class i and class j. Σ_i and Σ_j are the covariance of class i and class j respectively. A higher SI indicates the sEMG features of different motion classes are more distinguishable. That is, the feature extracted is more suitable for sEMG pattern recognition.

2) Classification: The linear discriminative analysis (L-DA) [13] is adopted to classify the thirteen motion classes. It has equivalent performance comparing to other complex classifiers while needs less computing time. Half of the 20 trials data are used as training data to construct the classifier and the other half are used as testing data. The performance of the constructed classifier is measured by the classification error, which is defined as



(a)



(b)

Fig. 3. Autoregressive power spectrum of sEMG signals (a) and its logarithmic transformation (b). Horizontal axis is normalized to 1000 Hz (half of sample rate). Yellow area means frequency band (20-450 Hz) used to extract feature.

$$\frac{\text{Number of falsely classfication samples}}{\text{Total number of testing samples}} \times 100(\%) \qquad (5)$$

Three different classifiers are constructed by the three different features (TDS, ARC and ARPS). Their performances are compared to inspect if the new feature extraction method proposed can improve the sEMG classification.

III. Results

The SI of the three sEMG features are summarized in Table I. The SI of ARPS is the highest for every participant (average 77.77). This shows that the ARPS has superiority for sEMG classification.

Fig. 4 shows the classification errors over five participants by using the three sEMG features. For every participant, the ARPS obtains the lowest classification error. The ARC has better performance than the TDS. In addition, the difference of classification error among the participants is significant (for example, see the difference between P2 and P3). This may be attributed to the different sEMG experiment experiences among them [16]. The average classification errors of TDS, ARC, and ARPS across five participants are 8.43%, 6.39%, 5.00% respectively as showed in Fig. 5. Owing to the significantly different performance among participants,

TABLE I

Separability index of three sEMG features

Feat.	P1	P2	P3	P4	P5	Mean
TDS	33.52	28.30	33.57	28.12	26.17	29.94
ARC	52.38	30.70	26.95	24.87	30.36	33.05
ARPS	119.33	62.81	88.26	48.91	69.57	77.77

the two-way analysis of variance is adopted. The analysis shows the classfication error of ARPS is significantly lower than that of TDS ($p = 0.01$) and that of ARC ($p = 0.02$).

Fig. 6 shows the average classification errors of specific motion classes. Comparing with TDS, the classification error of each motion class of ARPS is lower except the key grip. Comparing with ARC, the classification error of each motion class of ARPS is lower except the wrist flexion and fine pinch. The most evident improvements between ARPS and ARC occur in the fist, radial deviation and ball grasp. In addition, the classification errors of fine hand movements such as key grip and ball grasp are higher than that of raw hand movements or wrist movements such as open hand and wrist extension. How to extract more sEMG information about the fine hand movements from the bulk of forearm is still an open issue. This is very important to achieve the multifunctional prosthetic control for the transradial amputees.

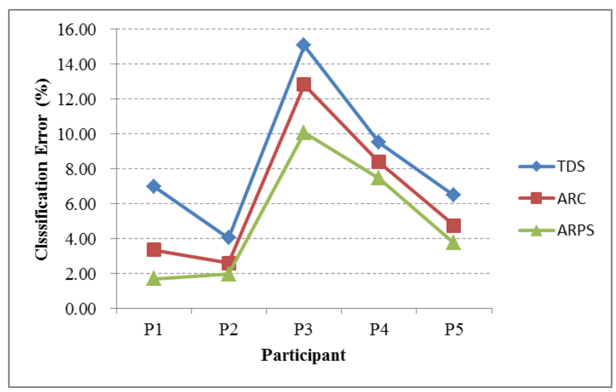


Fig. 4. Comparing classification errors of five participants among three sEMG features, TDS, ARC and ARPS. Horizontal axis means participants.

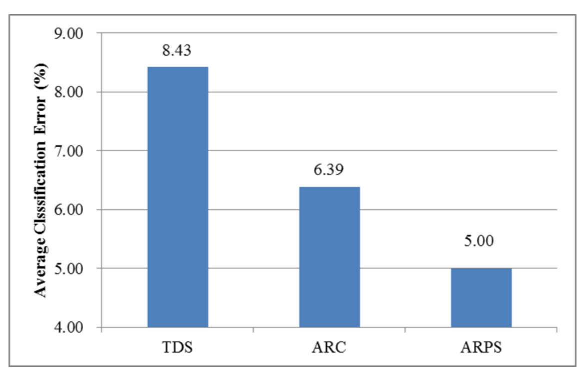


Fig. 5. Comparing average classification errors among three sEMG features, TDS, ARC and ARPS.

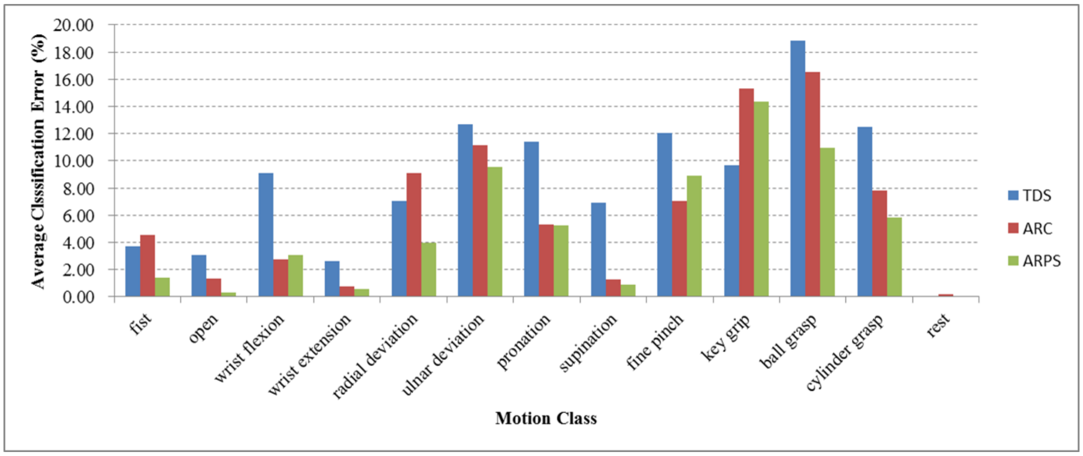


Fig. 6. Comparing average classification errors of specific motion classes among three sEMG features, TDS, ARC and ARPS.

IV. Discussion and Conclusion

The commonly used feature extraction method based on autoregressive model employs the autoregressive coefficients as the pattern of the sEMG signals. In this study, we proposed a new sEMG feature extraction method based on autoregressive power spectrum. A metric—SI based on Bhattacharyya distance which is independent of specific classifier shows the superiority of the new feature for recognizing different motions. In addition, the new feature, ARPS, obtains the lowest classification error (average 5.00%) when the LDA is constructed comparing with other two features (average 8.43% and 6.39%). Actually, the ARC feature and the ARPS feature are both based on autoregressive model. The reason that the ARPS feature outperforms the ARC feature may be the following two points.

- The denominator in the right side of the equation (2) contains all the autoregressive coefficients. Therefore the ARPS extracts more information from the sEMG signals than the ARC, that is, the power of innovation $\hat{\rho}_e$. This additional information may contribute to the discrimination of different motion classes.
- The logarithmic transformation is adopted and only the frequency band of 20-450 Hz is used to extract the ARPS feature. These steps can further reduce the effect of noise and make the feature more robust.

In conclusion, the new sEMG feature extraction method proposed here is effective and suitable for the sEMG pattern recognition.

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