35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

# Improved Discrete Fourier Transform Based Spectral Feature for Surface Electromyogram Signal Classification*

Jiayuan He, *Student Member, IEEE,* Dingguo Zhang, *Member, IEEE,* Xinjun Sheng, *Member, IEEE,* Jianjun Meng, *Student Member, IEEE,* and Xiangyang Zhu, *Member, IEEE,*

***Abstract*— An improved discrete Fourier transform (iDFT) is presented in this study as a novel feature for surface electromyogram (sEMG) pattern classification. It employs the principle that the spectrum of sEMG signals changes regarding different motions. iDFT feature focuses on global information of local bands to increase the inter-class distance. The experiment results showed that iDFT feature had a better separability than two other spectral features, auto regression (AR) and Power spectral density (PSD), both on experienced and inexperienced subjects. The optimal bandwidth is between 30 and 50 Hz and influence of division methods is not significant. With the low computation cost and property of insensitivity to sampling frequency, our proposed method provides a competitive choice for prosthetic control.**

## I. INTRODUCTION

Surface electromyogram (sEMG) signal, collected by electrodes attached to the skin, provides an important input for controlling electrically powered prostheses [1]. Many commercially available myoelectric systems employ a relatively simple scheme of encoding the amplitude of sEMG to control prosthetic devices such as a hand or wrist. The major problem of this approach is that it can not provide sufficient information to control more than one functions reliably. However, controlling multiple function is the requirement of amputees with high-level limb deficiencies [2]. To increase the number of prosthesis functions, researchers have explored a pattern recognition-based approach which can extract a wealth of control information from the sEMG signal [3]. Recently, many State-of-the-art methods have been proposed to improve the performance of the pattern recognition-based systems [2],[3].

The myoelectric control scheme based on pattern recognition includes two major parts: feature extraction and classification. Previous studies have shown that the representation of the sEMG signal plays an important role in improving the performance of myoelectric pattern recognition systems [4]. Features are classified into three categories: time domain, frequency domain, and time-frequency domain [5]. The frequency domain feature is based on the principle that the spectrum of sEMG signal changes with different limb functions. Such features like auto regression (AR) coefficients, have achieved high classification accuracy. However, performances of other representations of sEMG spectrum, such as direct use of Fourier transform [6], mean and medium frequency based on power spectral density (PSD) [5],[7], are all inferior to AR.

In this work, we used the Fourier spectrum and improved the representation based on discrete Fourier transform (DFT) for sEMG classification. The mechanism of iDFT feature was investigated and the separability was compared with two other spectral features, AR and PSD. Two metrics were introduced to quantify feature space changes between AR and iDFT. Then, we studied the influences of bandwidth and sampling frequency. Finally, some issues were discussed and a conclusion was drawn.

## II. METHODOLOGY

### A. Algorithm

According to literature [8], the spectral form of Euclidean distance between two different AR coefficients of time series model is given by

$$d_{AR}^2 = \int_{-\pi}^{\pi} |H_t(e^{j\omega}) - H_r(e^{j\omega})|^2 |A_t(e^{j\omega})|^2 |A_r(e^{j\omega})|^2 d\omega / 2\pi. \tag{1}$$

where

$$A_x(e^{j\omega}) = 1 + \sum_{i=1}^{P} a_{xi} e^{-ji\omega}. \tag{2}$$

$a_{xi}$ being AR coefficients, $x$ denoting $t$ or $r$.

$H_t(e^{j\omega})$ and $H_r(e^{j\omega})$ in (2) are the Fourier transforms of the test and reference signals respectively. It shows that the distance between two different AR coefficients in frequency domain is dominated by the difference of Fourier transforms of two signals, comparing the amplitude at the specific point. AR feature focuses on local information of sEMG spectrum.

Other representations like mean and medium frequency, focus on the global spectrum, neglecting its local information. This makes some details lost and degrades performance [5].

Enlightened by these two methods, we proposed a new representation based on DFT, iDFT, to better extract information form sEMG spectrum.

After calculation of DFT, the spectrum is divided into $L$ segments. Suppose that starting frequency and ending frequency of the $i$th segment are $f_{i,1}$ and $f_{i,n_i}$. Compute

*This work was supported by the National Basic Research Program (973 Program) of China (Grant No. 2011CB013305) and the Science and Technology Commission of Shanghai Municipality (No.11JC1406000).

All the authors are with the State Key Laboratory of Mechanical System and Vibration, Shanghai Jiao Tong University, Shanghai 200240, China. The authors emails are : hejiayuan@sjtu.edu.cn, dgzhang@sjtu.edu.cn, xjsheng@sjtu.edu.cn, mengjianjunxs008@gmail.com,mexyzhu@sjtu.edu.cn.

average amplitude of the segment and apply a non-linear logarithm transform to the value to ensure smoothness. iDFT feature is given by

$$iDFT_i = log(\sum_{j=1}^{n_i} \frac{|X(f_{i,j})|}{n_i}), \qquad i = 1, 2, \cdots, L. \tag{3}$$

Consider the following spectral measure

$$\begin{aligned} d^2_{iDFT} &= \sum_{i=1}^{L} [iDFT_{ti} - iDFT_{ri}]^2 \\ &= \sum_{i=1}^{L} \{log[\sum_{j=1}^{n_i} |Xt(f_{i,j})|/n_i] - log[\sum_{j=1}^{n_i} |Xr(f_{i,j})|/n_i]\}^2 \end{aligned} \tag{4}$$

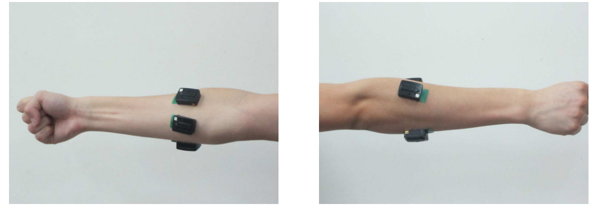
We can see in (4) that it is the global information of a local band that iDF pays attention to, neither global nor local information of the entire spectrum. It tries to make a balance between two extremes. So the length of segments is important. Good segmentation will hide differences within the same class, and on the other hand, keep differences between different classes. Meanwhile, since only average value is calculated, the influence of sampling frequency, which dominates frequency resolution, has a little impact on classification.

### B. Data Collection

Four able-bodied subjects (three males, one female, aged from 20 to 30 years old) participated in the study. Two of the subjects had no prior experience of EMG experiments. And the other two were experienced. Informed consent was obtained from the subjects and the procedures were in accordance with the Declaration of Helsinki.

Ten classes of wrist and hand motions plus a class of no movement were considered in the study. The ten motion classes were hand and wrist motions, pronation, supination, hand closing, hand opening, radial flexion, ulnar flexion, flexion, extension, palmar prehension and lateral prehension. The commercial myoelectric system, TrignoTM Wireless system (Delsys Inc., 20-450 Hz band pass filter), was used to collect EMG data. Four wireless electrodes were placed around the circumference of the forearm one-third of the distance from the elbow to the wrist, which is shown in Fig. 1. They were located on the extensor carpi ulnaris, flexor carpi radialis, extensor carpi radialis longus, flexor carpi ulnaris, respectively. The sampling frequency was set to 2 kHz. During the experiment, all participants naturally extended their arms toward the ground. They were instructed to perform each motion sequentially with a comfortable and consistent level of effort. EMG data were collected in twenty consecutive trials. In each trial, one motion was held for 4 s and all the motions were repeated once. Only the steady state was recorded. There was a 4 s rest between two neighboring motion classes to avoid fatigue.

200 ms analysis windows were used with 50 ms of overlap. In this way 13860 samples were obtained for each subject. This was enough for a proper statistical evaluation.



(a) (b)

Fig. 1. Placement of electrodes on the forearm: (a) anterior view, (b) posterior view.

## III. Results

### A. Evaluation of separability of features

In this study, the sixth-order AR model was chosen for it was commonly used. The influence of model order on the recognition rate was investigated in literature [8] and it showed the recognition rate would be slightly improved as the order increased. So the eleventh-order was addressed. And another frequency domain feature set, mean frequency, variance and average amplitude based on PSD [7], was also compared.

Since the signal was band-pass filtered (20-450Hz), the frequency band was divided into six segments, which were 20-92Hz, 92-163Hz, 163-235Hz, 235-307Hz, 307-378Hz, 378-450Hz. Each was about 70Hz. Linear discriminant analysis (LDA) classifier was selected for its low computation cost. The second-order cross validation method was used for the evaluation of recognition rate. Results are showed in Fig. 2, where ES1, ES2 represent the experienced subjects and IE1 and IE2 are the inexperienced. It can be seen that the error rate of iDFT feature is lower than AR11, AR6 and PSD, independent of experience.

The motions generated by subjects with and without experience are different [9]. Its influence should be taken into account. So a two way ANOVA was applied on the error rate using the features and subjects as factors. The significance level was 0.0231, 0.0374, and 0.0391 for iDFT with AR11, AR6 and PSD, respectively. It showed that the performance of iDFT feature was significantly better than the others.

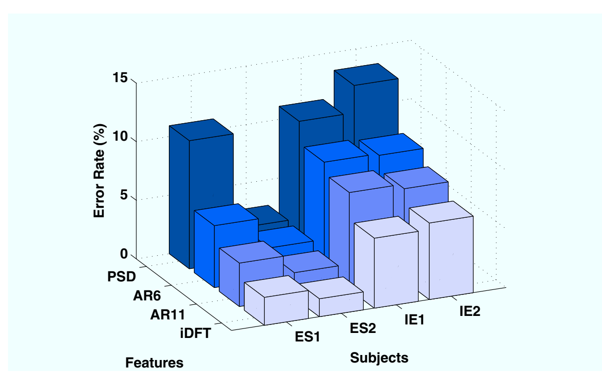



Fig. 2. Error rate of different features for each subject. ES1, ES2 are experienced and IE1 and IE2 are inexperienced.

The separability may be improved by reducing intra-class variability or by increasing inter-class distance. To quantify the changes of feature space, two metrics, the inter-class distance and intra-class distance, were introduced. The distance between class $i$ and $j$ is defined as:

$$D_{ij} = \frac{1}{2}\sqrt{(c_i - c_j)(\frac{S_i + S_j}{2})^{-1}(c_i - c_j)} \tag{5}$$

where $c_i$ and $c_j$ are the centroid of class $i$ and $j$, $S_i$ and $S_j$ are the covariance of two classes respectively.

The inter-class distance is defined as:

$$DT = \frac{1}{C}\sum_{j=1}^{C}(\min_{i \neq j} D_{ij}) \tag{6}$$

where $C$ is the number of class.

The intra-class distance is defined as:

$$DA = \frac{1}{C}\sum_{i=1}^{C}\frac{1}{n_i}\sum_{k=1}^{n_i}\sqrt{(v_{ik} - c_i)(S_i)^{-1}(v_{ik} - c_i)} \tag{7}$$

where $n_i$ is the number of feature vectors in class $i$, $v_{ik}$ is the $k$th feature vector of class $i$. A higher $DT$ and a lower $DA$ results in a better classification performance.

Mahalanobis distance not Euclidean distances are used to avoid the influence of different units. Only iDFT and AR6 are considered for the affect of feature dimension. The inter-class and intra-class distances are showed in Table I and Table II respectively.

TABLE I

INTER-CLASS DISTANCE OF DIFFERENT FEATURES FOR EACH SUBJECT

| | ES1 | ES2 | IE1 | IE2 |
|---|---|---|---|---|
| iDFT | 8.72 | 9.26 | 6.82 | 7.82 |
| AR6 | 8.29 | 8.89 | 6.12 | 6.76 |

TABLE II

INTRA-CLASS DISTANCE OF DIFFERENT FEATURES FOR EACH SUBJECT

| | ES1 | ES2 | IE1 | IE2 |
|---|---|---|---|---|
| iDFT | 5.03 | 5.25 | 5.27 | 5.09 |
| AR6 | 5.01 | 5.07 | 5.12 | 5.61 |

It can be seen in Table I that the inter-class distance of iDFT feature is larger than AR6. However, the intra-class distance of iDFT is also larger than AR6. It means iDFT feature increases the classification performance by enlarging the distance between classes. Meanwhile, the intra-class dispersion is also a little increased, but its degree is not as great as inter-class. So the separability is improved.

### B. Influence of parameters of iDFT feature

The number and the length of segments are two important parameters of iDFT feature.

With the same length of all the segments, 11 different bandwidths, ranging from 5 Hz to 430 Hz, are chosen to find the optimal bandwidth. In Fig. 3, we can see that the optimal bandwidth of four subjects lies in the middle, approximately between 30 Hz and 50 Hz. The influence of big bandwidth is greater than the small bandwidth.

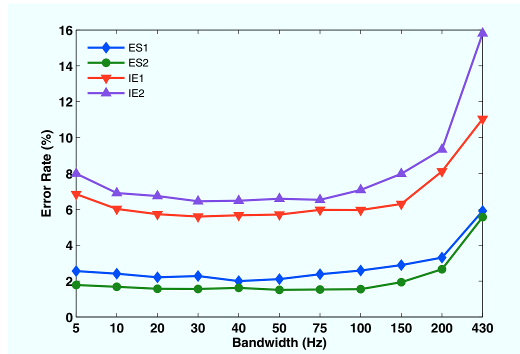



Fig. 3. Error rate of different bandwidth for each subject. The entire band is from 20 Hz to 450 Hz and it is divided equally.

Then, the number of segments is fixed to six to find the difference between different methods of band division. Three methods are introduced. The first method is that the low-frequency band is divided intensively, which labeled as low-frequency. The second is that the high-frequency band is divided intensively, labeled as high-frequency. The third is that the entire band is divided equally, labeled as medium-frequency. All the frequency boundary points are shown in Table III.

TABLE III

FREQUENCY OF BOUNDARY POINTS OF THREE DIFFERENT METHODS

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Low-frequency | 20 | 32 | 68 | 128 | 211 | 319 | 450 |
| Medium-frequency | 20 | 92 | 163 | 235 | 307 | 378 | 450 |
| High-frequency | 20 | 151 | 259 | 343 | 402 | 438 | 450 |

The error rates of all three methods can be seen in Fig. 4. The performance of medium-frequency method is slightly better than the other two, but none of three has the advantage over the others. A two way ANOVA is applied using the methods and subjects as factors. The result ($p = 0.7604$) shows there is no significant difference in performance between the band division methods. For computation convenience, the medium-frequency method is recommended.

### C. Influence of Sampling Frequency

The signal is down-sampled to 1000Hz to evaluate the influence of sampling frequency. Other processing procedures are the same. Fig. 5 shows the comparison of error rate between data of different sampling frequencies. For AR6 and AR11 feature, error rates with 1000 Hz sampling frequency are much greater than 2000 Hz. The reduction of sampling frequency has an impact on the performance of AR feature. However, as for iDFT and PSD feature, the error rates are nearly identical. They are not sensitive to sampling frequency.

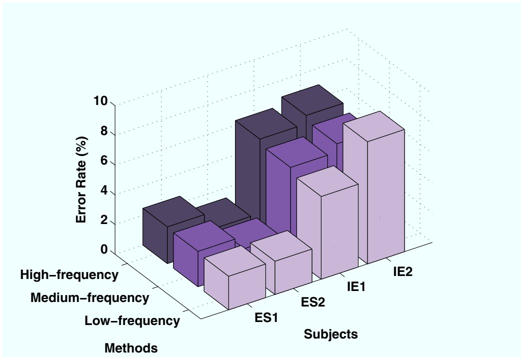



Fig. 4. Error rate of different band division methods for each subject. Low-frequency means the low-frequency band is divided intensively. High-frequency means the high-frequency band is divided intensively. Medium-frequency means the band is divided into six parts equally.

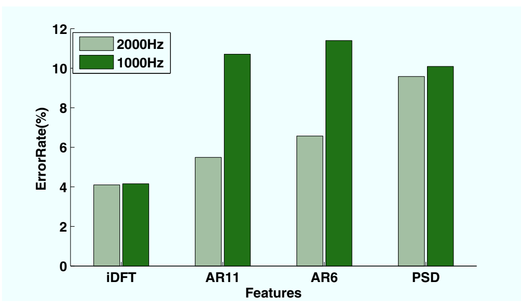



Fig. 5. Comparison of error rate of different sampling frequency for four features.The methods and parameters keep the same.

## IV. Discussion

Bandwidth was an important parameter of iDFT feature. As the band was represented by its average amplitude, information of the specific point was lost. At first, information mainly about differences within the motion class were ignored, which decreased the error rate. As the bandwidth increased, information of differences between classes was lost, too. Then error rate began to rise. We can see form Table I and Table II that iDFT feature mainly enlarged the inter-class distance to improve performance. Previous study showed that inter-class distance of experienced subjects was larger than that of inexperienced subjects, while their intra-class distances were similar [9]. So the effect for inexperienced subjects was more significant than the experienced, when bandwidth increased from 5 Hz to 40 Hz in Fig. 3.

More information was kept if a frequency band is divided intensively. So different division methods keep information of different bands. However, results were not significant in Fig. 4. It meant that in this study, the discriminative information of sEMG signal lied in the entire band.

As it is known, reduction of sampling frequency would bring about the decrease of frequency resolution. It had an effect on the estimation of local spectrum information. So error rates of AR feature increased dramatically. However, it had little effect on the estimation of global information. Thus, performances of iDFT and PSD were similar.

We noted that the similar feature was used in [6] and its performance was not as good as AR11, which was opposite to our results. There existed differences. In their work, the bandwidth was only 12.5 Hz and was chosen heuristically, without any analysis. The bandwidth was obviously not enough according to our results. To our best knowledge this was the first time to analyze the separability of iDFT feature and influence of its parameters. Meanwhile, we took the logarithm to ensure the smoothness and enhanced the stationarity of the data, which would help increase the recognition rate further.

The computation cost was an important issue for the myoelectric prosthesis control. The long processing time could cause large controller delays which would degrade the prosthesis performance. The proposed method had the advantage of convenient implementation with the use of fast Fourier transform (FFT) algorithms. With low misclassification error and insensitivity to sampling frequency, iDFT feature was a promising feature for prosthetic control.

## V. Conclusions

This work presented a good representation based on sEMG spectrum, iDFT. It focused on the global information of local band and achieved a better separability than two other frequency domain features, AR and PSD. The insensitivity to sampling frequency and low computation cost made the proposed feature a good option for prosthetic control.

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