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Classification of Grip Configuration Using Surface EMG

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Abstract: Surface EMG is a bio-potential signal from muscles, which has been used in various fields such as medical and engineering applications. Among them is classification of hand configurations using the surface EMG from forearm muscles because the surface EMG on the forearm is related to wrist and hand motion. In this paper, four hand grip configuations are classified depending on which fingers are used for the grasping of a cylindrical shape object. The experimental results show the feasibility of classifying grip configurations using surface EMG signals on the forearm.

Keywords: Surface EMG, Hand motion classify.

1. INTRODUCTION

Electromyogram(EMG) signals are bio-electrical signals that occur during muscle contraction. The value of EMG is the sum of the values of the action potential signal of the muscle fiber's motor unit. Surface EMG (sEMG) signals are the EMG signals measured on the skin. The sEMG signal is widely used in medical diagnosis and engineering applications because it can be noninvasively obtained [1], [2]. Various methods of feature extraction for sEMG have been developed using transfoms such as Fourier transform (FT), short time fourier transform (STFT), and wavelet transform (WT)[3]. Among them, the wavelet transform is the time-frequency analysis method of non-stationary signals. For instance, it has been applied on sEMG signals to classify the back pains [4] and to identify the contraction of the leg muscles during walking [5]. It was also used in the development of knee joint assistive device using the sEMG singals from thigh muscles[6].

The feature vector extracted from sEMG signals by wavelet transform has high dimensional data with noise and delay from the transformation. Therefore, data reduction techniques are applied on the extracted feature vector such as principal component analysis (PCA)[7], independent component analysis (ICA), and Nonnegative matrix factorization (NMF). Among them, the nonnegative matrix factorization (NMF) has been used on the signals of Electroencephalogram(EEG)[8] and in the face detection application [9]. These reduced feature vector can then be used for classification of specific purpose using the methods such as self-organizing feature map (SOFM), multi-layer perception(MLP) [10], and linear discriminant analysis (LDA) [7].

In this paper, four different grip configurations are classified by using sEMG signals on the forearm as shown in Fig. 1. First, the feature vectors are extracted from sEMG signals by using wavelet transformation, which dimension is then reduced by nonnegative matrix factorization. Finally, linear discriminant analysis is used to identify the grip configuration of the hand.

The paper is organized as follows. The measurement and pre-processing of sEMG signals are described in Section II. Then, Section III explains the feature extraction and classfication. The experimental results are presented in Section IV. And the paper is concluded in Section V.

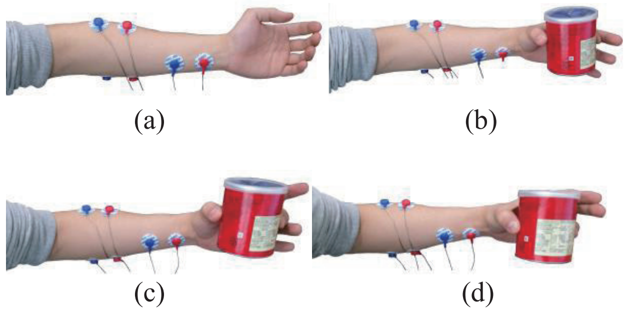

Fig. 1 Four types of hand grip configurations: (a) No grip (b) grip with thumb and forefinger. (c) grip with thumb and middlefinger (d) grip with thumb and ringfiger

2. MEASUREMENT OF EMG SIGNAL

2.1 Acquisition of sEMG signal

Three parts of forearm muscles are selected for sEMG measurements: flexor digitorum superficialis (FDS), flexor digitorum profundus (FDP), extensor digitorum (ED). FDS and FDP are related with the movement of the thumb, forefinger, middlefinger, and ringfinger. ED produces sEMG signals from the movement of thumb, middlefinger, and ringfinge has relationship[11]. These muscles are represented on Fig. 2.

2.2 sEMG signal preprocessing

The range of sEMG signals is within $\pm 10mV$ and the frequency range is $0 \sim 1000$Hz. However, the dominant energy of the signals is within $20 \sim 500$Hz. A

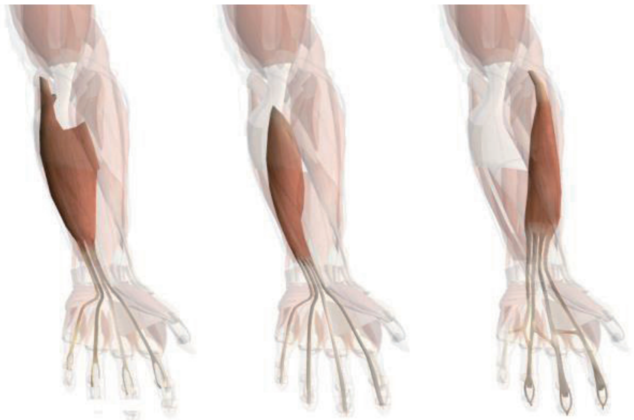

Fig. 2 Hand grip motion muscle: (a) FDS (b) FDP (c) ED.

lowpass and highpass filter (1^{st} order active filter) is designed to filter out the noise in other frequency regions and the filtered signal is amplified to $0 \sim \pm 5V$ and $19.175 \sim 530$Hz. This signal is then sampled at $1024Hz$.

Now, the digital signals are filtered by bandpass and notch filters because the frequency response of the analog filter has ripples at the frequency cutting edge. A notch filter is applied to cut off the power noise at 60Hz. The slide window with the size of 256 samples is used for feature extraction in the next section.

3. FEATURE EXTRACTION AND CLASSIFICATION

3.1 Feature extraction

sEMG signals are non-stationary signals, which have complicated time-frequency chracteristics. For this reason, the feature vectors can be extracted using time-frequency transformations such as fourier transform, short time fourier transform, and wavelet transform. Among them, wavelet tranform is used in this paper because it can reflect small variation of data and independent on the length of the data compared to fourier transformation. It also has better time-frequency resolution which can lead to more precise time-frequency representation than short-time fourier transformation [14].

To apply to the digital sEMG signals obtained from the pre-processing, discrete wavelet transform is used for multi-resolution analysis (MRA) [15]. Using the discrete wavelet transform, high frequency signal is separated by detail-coefficient based mother wavelet, and low frequency signal is separated by approximation-coefficient based mother wavelet [16] as the following.

$$f_{low}[n] = \sum_{k=-\infty}^{\infty} x[k]\, d[2n-k] \tag{1}$$

$$f_{high}[n] = \sum_{k=-\infty}^{\infty} x[k]\, a[2n-k] \tag{2}$$

where $x[n]$ is the input data. $d[2n-k]$ and $a[2n-k]$ denote the detail-coefficient based mother wavelet and the approximation-coefficient based mother wavelet, respectively [15]. The 7^{th} order daubechis mother wavelet is used as the mother wavelet for sEMG in this paper and the 4^{th} order decomposition is applied to generate five decomposed signals. Then, the signals are reconstructed by using inverse discrete wavelet tranform to reduce the noise of decomposed signal [17]. The results of decomposition and reconstruction are plotted in Fig. 3. The root-mean-square values of the five decomposed signals are used as features on each sensor. Therefore, a feature vector for grip configuration has fifteen RMS values.

3.2 Classification

The dimension of the feature vector is reduced by non-negative matrix factorization before it is used for classification.

$$\begin{gathered} X = WH + E, \\ X \in \Re^{m\times n}, W \in \Re^{m\times k}, H \in \Re^{k\times n}, E \in \Re^{m\times n} \end{gathered} \tag{3}$$

where X is the input data matrix for training. The row vectors of this matrix are the feature vectors. The number of rows indicate the number of training data. The matrix W is the basis matrix and H is the decision matrix composed by training data set. The matrix E is an error matrix. The number k represents the reduced dimension of the feature vectors such that the ratio between the sum of the singular values of the reduced input matrix and that of the input matrix is set to be a certain value. This ratio is set to 99% in our experiment. The error matrix E is minimized by multiplicative updates rule iteration method [18].

Now, when we have a probe data set Y, the feature vectors of the probe data for classification are obtained by

$$P = W^{+}Y \tag{4}$$

Once the matrices P and H for the probe data and training data are obtained, linear discrimant analysis is used to classify the four grip configurations.

4. EXPERIMENT RESULT

The experiments were conducted to recognize the four configurations in Fig. 1. The training data was obtained by gathering sEMG signals during 30 seconds for one grip configuration. 240 feature vectors are obtained for each grip configurations with each window size of 256 samples. The size of a feature vector was 15 as described in the previous section. Therefore, the matrix X in Eq. (3) has the dimension of 15×240 and the dimension of the reduced matrix H is 13×240 with $k = 13$.

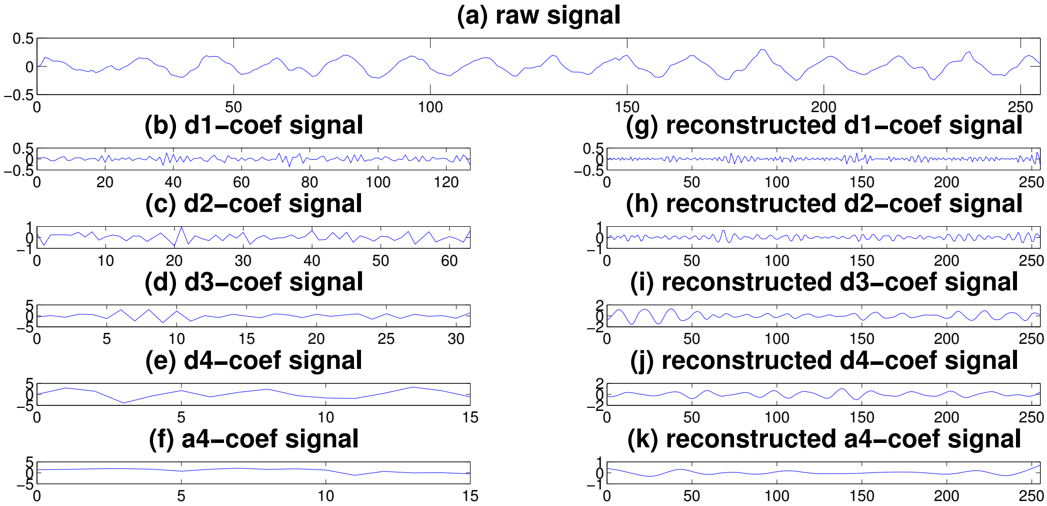

Fig. 3 Single sEMG decomposition and reconstruction: x-axis is time (seconds) and y-axis is amplitude (voltage) (a) Raw EMG signal (b)-(f) reconstructed coefficients of raw EMG signals (g)-(k) decomposed coefficients of raw EMG signals

Ten trials of the grip recognition were conducted. In each trial, the sEMG signals were measured for 30 seconds for one grip configuration, which generate the matrix H for the probe data that has the same size as the matrix P for the training data. The overall flow chart of operation is shown in the Fig. 4.

Fig. 4 Entire flow chart of hand grip motion classification system.

Table 1 Classification results using NMF and PCA algorithms.

	WT-NMF-LDA	WT-PCA-LDA
Trial1	100%	99.58%
Trial2	93.33%	90.42%
Trial3	100%	100%
Trial4	100%	100%
Trial5	97.08%	97.92%
Trial6	97.50%	97.50%
Trial7	99.58%	99.58%
Trial8	99.17%	98.75%
Trial9	95.42%	95.42%
Trial10	99.58%	99.58%
Average	98.17%	97.88%

Table 1 show the result of our experiments. The result is compared with the one with PCA instead of NMF. It can be noted that the result of using NMF has slightly higher rate than that of using PCA.

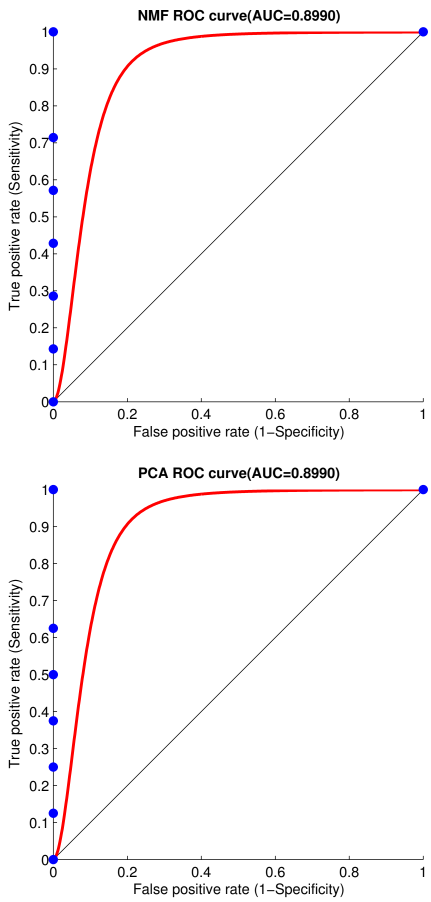

Fig. 5 ROC curve of NMF based algorithm and PCA based algorithm.

The Receiver Operating Characteristic(ROC) curves [21] of the results are also plotted in Fig. 5, respectively. Both algorithms show similiar classification rate since two graphs have approximately the same area under the ROC curve (AUC), which is 0.8990.

5. CONCLUSION

Hand grip configurations are classified using three sEMG signals on the forearm. Wavelet transformation, nonegavie matrix factorization, linear discriment analsys are used for feature extraction, dimension reduction, and classification, respectively. For 10 trials, all the recognition rates were over 90% and the total average was 98.17%. This result was also compared with that of using PCA for dimension reduction. The future research goal is to recognize different grip force levels as well as different grip configurations.

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