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Recognition of Hand Motions via Surface EMG Signal with Rough Entropy

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Abstract—**The rough entropy (RoughEn) is developed based on the rough set theory. It has the advantage of low computational complexity, because there is no parameter to set in RoughEn. In this paper, we characterized the feature of surface electromyography (SEMG) signal with RoughEn and then used support vector machine to classify six different hand motions. The sample entropy, wavelet entropy and approximate entropy were compared with RoughEn to evaluate the performance of characterizing SEMG signals. The experimental results indicated that the RoughEn-based classification outperformed other entropy based methods for recognizing six hand motions from four-channel SEMG signals with the best recognition accuracy of 95.19 ± 2.99%. The results suggest that RoughEn has the potential to be used in the SEMG-based prosthetic control as a method of feature extraction.**

I. Introduction

SURFACE electromyography (SEMG) controlled prosthetic hand has received widespread use mainly due to the advantage of autonomous nature of control [1][2]. In the implementation of multifunctional prosthetic control by SEMG, pattern recognition plays a key role, and it includes two crucial steps: feature extraction and classification [1]. Various feature extraction methods have been proposed for SEMG-based prosthetic control, which can be roughly classified into three categories, namely time domain, frequency domain, and time–frequency domain methods [1][3].

SEMG signal has shown some kind of nonlinear or even chaotic behavior [4][5]. Therefore, it is reasonable to apply the nonlinear time series analysis methods to SEMG signal, such as the fractal dimension, correlation dimension, correlation integral, Lyapunov spectrum, Kaplan–Yorke dimension and recurrence plot analysis [4][6]. However, these methods may result in spurious results when they are applied to short or irregular sequences of real experimental data [4][6]. Moreover, the noise is unavoidable in SEMG due to various factors, affecting the performance of these methods.

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Since Pincus proposed the approximate entropy (ApEn) to measure the system complexity [7][8], it has been widely used for biomedical signals, because it is applicable to short and noisy dataset. Entropy, such as the ApEn, sample entropy (SampEn) and wavelet entropy (WaveletEn), has been applied to characterize SEMG for analysis or classification [9][10][11]. However, the parameter selection for ApEn, WaveletEn and SampEn is still subjective and usually needs repetitive experiments to obtain the 'optimal' parameters.

Recently, the rough entropy (RoughEn) has been proposed based on the rough set theory (RST) [12]. RST represents a mathematical approach to vagueness and uncertainty of imperfect knowledge [13]. Therefore, RoughEn can characterize the vagueness and uncertainty of signals or images. RoughEn has been applied mainly in image processing, such as object extraction [12], object tracking [14] and image segmentation [15]. However, it is seldom used for biomedical signals, except Gene analysis [16].

In this paper, we propose a method for discriminating different hand motions from SEMG signals with RoughEn and support vector machine (SVM).

II. Methods

A. Rough Entropy

RST is based on the assumption that with every object of the universe there is associated a certain amount of information (data, knowledge), expressed by means of some attributes used for object description [17].

The theory of RoughEn is introduced as follows [18][19]. Let K=(U,R) be an approximation space, where U is a non-empty and finite set called the universe; R is a partition of U, or an equivalence relation on U. Then the approximation space K can be regarded as a knowledge base about U. Let

$$R=\{R_1,R_2,\ldots,R_m\} \tag{1}$$

Given a partition R, and a subset $X \subseteq U$, we can define a lower approximation of X in U and an upper approximation of X in U by the following expressions:

$$\underline{R}X = \bigcup\{R_i \in R \mid R_i \subseteq X\} \tag{2}$$

and

$$\overline{R}X = \bigcup\{R_i \in R \mid R_i \cap X \neq \phi\} \tag{3}$$

where $\underline{R}X$ is the lower approximation and $\overline{R}X$ is the upper approximation.

Both the lower approximation and upper approximation are unions of some equivalence classes. More precisely, $\underline{R}X$ is the union of those equivalence classes which are subsets of X, and $\overline{R}X$ is the union of those equivalence classes which have a non-empty intersection with X.

The RoughEn of knowledge R is defined by

$$RoughEn(R) = -\sum_{i=1}^{m} \frac{|R_i|}{|U|} \log_2 \frac{1}{|R_i|} \quad (4)$$

where $|R_i|/|U|$ represents the probability of equivalence class R_i within the universe U, and $1/|R_i|$ denotes the probability of one of the values in equivalence class R_i.

If $R=\hat{R}$, then the RoughEn of knowledge R achieves the minimum value 0.

If $R=\check{R}$, then the RoughEn of knowledge R achieves the maximum value $\log_2|U|$.

Obviously, when R is a partition of U, or an equivalence relation on U, we have that $0 \leq RoughEn(R) \leq \log_2|U|$.

In practical application, for an N sample time series $\{u(i):1\leq i\leq N\}$, the time series can be represented by U. If $u(i)$ and $u(j)$ $(i\neq j)$ are the same, they will belong to the same class R_i, where $|R_i|$ denotes the number of R_i set, namely $|R_i|=1/\text{card}(R_i)$.

B. SVM

SVM is a supervised machine learning algorithm proposed by Vapnik and his co-workers [20]. It aims at minimizing an upper bound of the generalization error through maximizing the margin between the separating hyperplane and the data. SVM is known to generalize well even in high dimensional spaces under small training sample conditions and has shown to be superior to traditional empirical risk minimization principle. SVM has been studied extensively for classification, regression and density estimation. In this work, the "one-against-one" strategy of SVM, which builds one SVM for each pair of classes, was adopted to classify different hand motions. More detailed information about this multiclass SVM can be found in [21].

III. EXPERIMENTS

A. Subjects

Six healthy young subjects participated in the experiment. None of them had any history of neuromuscular disorder. Each was given the written informed consent prior to the experiment.

B. Data Acquisition

Four channels of SEMG signals were recorded using the bipolar, Ag-AgCl, surface electrodes with 15 mm diameter and 20 mm center to center spacing. Skin surface of the area of interest was abraded with alcohol beforehand. The electrodes were placed on the forearm above the wrist flexors, extensors and each side of the forearm, approximately equidistant from the elbow and the wrist [22]. The reference electrode was placed on the proximal head of the ulna. The SEMG signals were digitally sampled at 1000 Hz with amplified gain of 2000, and filter bandwidth of 10 - 800 Hz.

Each subject was instructed to perform six different hand motions, namely wrist flexion (WF), wrist extension (WE), radial deviation (RD), ulnar deviation (UD), hand closing (HC) and hand opening (HO). Subjects performed each class of motions 60 trials and each contraction trial was held for 5 second durations. The initial hand position was in horizontal position for each subject, and it was consistent in each trial. Once the contraction was established, the SEMG data would be recorded. There is a 2 minute resting period after each motion to avoid muscle fatigue.

C. Signal Processing

The SEMG signals were segmented for each trial to calculate the entropy. Every segment lasted 1 second with 1024 points starting from the 2^{nd} second. For each subject, 30 segments in every class of motions were randomly selected, and totally 180 segments were grouped as training dataset to train SVM. The remaining segments were used as testing dataset to verify the performance of different entropies. The data used for training and testing are not overlapped.

In order to comprehensively evaluate the performance of RoughEn-based classification of different hand motions, we also adopted SampEn, WaveletEn and ApEn for comparison. All the SEMG segments were processed by the RoughEn, SampEn, WaveletEn and ApEn algorithms as SEMG features for classification. The parameters were obtained based on both the experiments and the relative paper. The m and r values were 2 and 0.2 for SampEn and ApEn, respectively, and the Haar wavelet was selected for WaveletEn with three decomposition levels.

The LIBSVM software was used for classification in this work, which had been widely used in many areas. RBF function was selected as the kernel function of SVM.

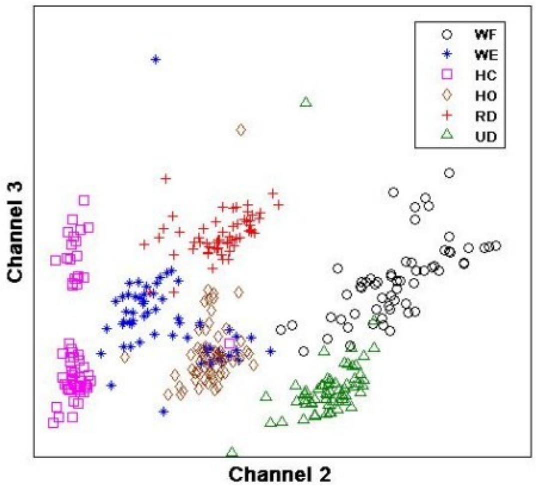
IV. RESULTS

A. Qualitative Feature Distribution

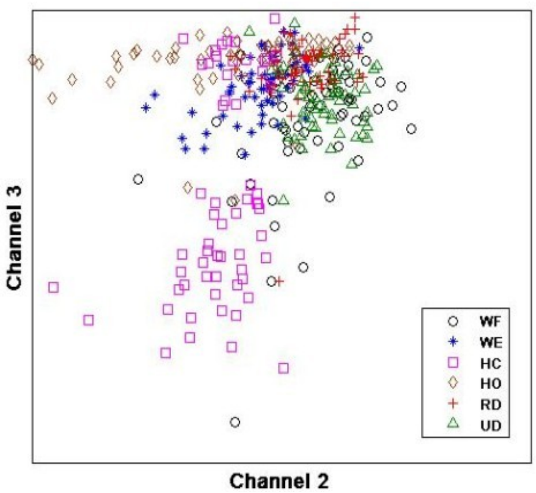
For an intuitive observation of the feature distributions of six known motions, we randomly selected the distributions in channel 2 and channel 3 for different entropies. As shown in Fig. 1, the abscissa represents the entropy values of SEMG from channel 2, and the ordinate refers to those from channel 3. We can find that points of the six motions in Fig. 1(b), 1(c) and 1(d) are not clearly distinguishable. The overlapped points indicate that it is difficult to discriminate six motions from SampEn, WaveletEn and ApEn. Distributions of points in Fig. 1(a) are much clearer at the boundaries, indicating that different motions can be potentially classified by RoughEn.

B. Quantitative Results

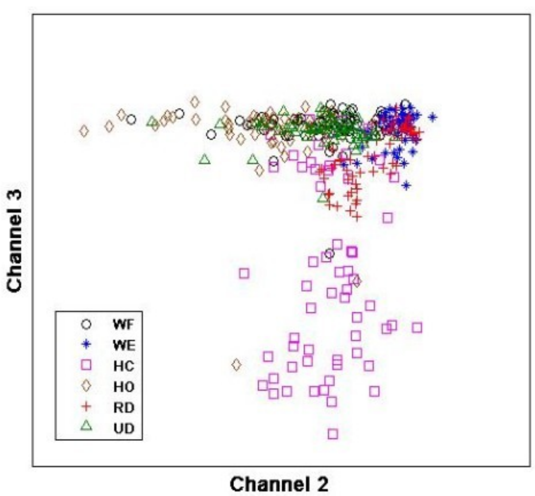
Table I shows the recognition accuracy of different entropy-based features in all kinds of channel combinations. The recognition accuracies of RoughEn are much better than those of other three entropies in every kind of channel combination. The best accuracy of RoughEn is 95.19±2.99% with four channel combination, and even with two channel combination, the best one is 82.13±7.19%, which is higher than the best results of other entropy based methods.



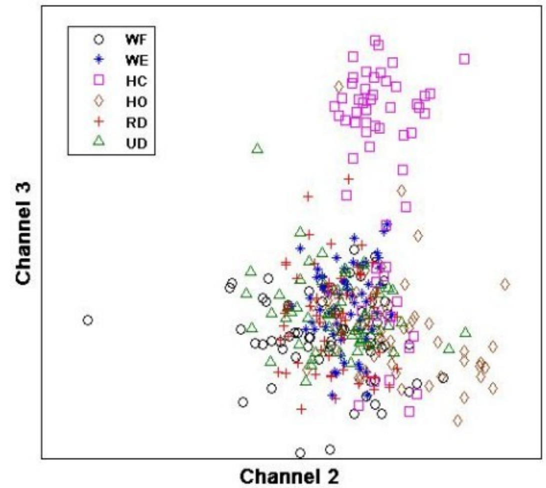
(a)



(b)



(c)



(d)

Fig. 1 Scatter plots of entropy values of two-channel SEMG signals for six motions, (a) distribution of RoughEn values; (b) distribution of SampEn values; (c) distribution of WaveletEn values; (d) distribution of ApEn values.

TABLE I
AVERAGE RECOGNITION ACCURACY OF DIFFERENT ENTROPY-BASED CLASSIFICATION

Channel Combination	RoughEn	SampEn
1&2	**80.56±9.45**	45.47±4.42
1&3	**67.50±11.31**	43.24±6.21
1&4	**70.56±12.41**	38.33±6.82
2&3	**84.08±7.74**	49.26±7.83
2&4	**82.13±7.19**	44.35±7.71
3&4	**81.67±10.33**	47.32±6.22
1&2&3	**89.17±5.26**	55.18±9.89
1&2&4	**89.63±5.46**	50.93±6.31
1&3&4	**85.37±11.11**	52.22±7.01
2&3&4	**92.69±4.91**	54.72±10.27
1&2&3&4	**95.19±2.99**	57.31±11.03

Channel Combination	WaveletEn	ApEn
1&2	59.63±9.32	36.85±4.20
1&3	55.10±10.32	39.45±6.80
1&4	59.07±11.61	39.35±8.00
2&3	54.07±9.33	36.67±9.11
2&4	46.48±9.88	35.74±4.40
3&4	52.22±10.35	41.57±8.96
1&2&3	68.89±9.09	41.67±9.41
1&2&4	69.72±9.70	44.35±6.10
1&3&4	67.96±9.64	48.61±9.08
2&3&4	62.59±11.63	42.87±8.50
1&2&3&4	76.67±11.93	49.17±9.09

V. DISCUSSION

In this paper, we described an entropy-based framework of recognizing six hand motions from SEMG signal. As shown in Table I, RoughEn-based motion recognition obtained most accurate classification, and outperformed other compared methods.

The most important advantage of RoughEn is that its computational complexity is very low, because there is no parameter to set in RoughEn. While in SampEn, WaveletEn and ApEn, the parameter selection is somewhat a subjective choice, and usually needs repetitive experiments to obtain the 'optimal' parameters, which is time-consuming. The low computational complexity makes it possible for RoughEn to be used in the real-time prosthetic control, which will be investigated in our further work.

RoughEn has been successfully applied in SEMG signal. Therefore, it has the potential to be applied to other physiological signals with short data length in noisy background, such as electroencephalogram and electrocardiogram, which will be studied in the future.

In this work, we use SVM, a very popular classification algorithm, as the classifier. Although the recognition results are satisfied to some extent, more classification algorithms should be involved to more comprehensively evaluate RoughEn as a characteristic feature of SEMG. Moreover, the real-time prosthetic control is always the purpose to develop prosthetic hands. But SVM is time-consuming, which may be not suitable for the real-time prosthetic control. We will study the feasibility of combining RoughEn with relevance vector machine (RVM) to realize real-time controlling of SEMG-based prosthesis, because RVM is more effective than SVM in time-cost.

VI. Conclusion

In conclusion, we proposed the RoughEn-based method for supervised classification of different hand motions from SEMG signal. The results indicated that RoughEn had better performance than all other entropies compared in this work to characterize SEMG features for hand motions, suggesting RoughEn has the potential to be used for controlling the SEMG-based multifunctional prosthesis.

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