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Characterization of Surface EMG with Cumulative Residual Entropy

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ABSTRACT

The cumulative residual entropy (CREn) is an alternative measure of uncertainty in a random variable. In this paper, we applied CREn as a feature extraction method to characterize six hand and wrist motions from four-channel surface electromyography (SEMG) signals. For comparison, fuzzy entropy, sample entropy and approximate entropy were also used to characterize the SEMG signals. The support vector machine (SVM) and linear discriminant analysis (LDA) were used to discriminate six hand and wrist motions in order to evaluate the performance of different entropies. The experimental results indicate that the CREn-based classification outperforms other entropy based methods with the best classification accuracy of is 97.17±1.97% by SVM and 93.56±4.13 by LDA. Furthermore, the computational complexity of CREn is lower than those of other entropies. It suggests that CREn has the potential to be applied as an effective feature extraction method in the control of SEMG-based multifunctional prosthesis.

Index Terms—Cumulative residual entropy, Surface electromyography, Classification

1. INTRODUCTION

Surface electromyography (SEMG) is the summation of motor unit action potentials from many muscle fibers under the electrodes during muscle contraction, representing the neuromuscular activities [1][2]. SEMG-based prosthetic hand, especially the multifunctional prosthetic hand, has received widespread attention primarily due to its advantage of autonomous nature of control [3].

Feature extraction plays a key role in implementing the SEMG-based multifunctional prosthetic control [3], though it is still a challenging problem due to its complexity, especially the multi-channel SEMG signals. Various feature extraction methods have been proposed for SEMG-based prosthetic control. These algorithms can be generally classified into three categories: time domain methods, frequency domain methods, and time-frequency domain methods [3].

SEMG signal has been proved to show some nonlinear or even chaotic behavior [4][5]. Therefore, it is reasonable to apply the nonlinear time series analysis methods, including the entropy measurement. The approximate entropy (AEn), which was first proposed by Pincus to measure the system complexity in short and noisy environment [6], has been successfully used in analyzing physiological and clinical signals [7]. Thereafter, other entropic measures have been applied to EMG as well, including cross-AEn [8], moving AEn [9], sample entropy (SEn) [10], fuzzy entropy (FEn) [11], multiscale entropy [12] and wavelet entropy [13]. However, the way of parameter choice in these entropies is still empirical and usually requires repeated experiment testing to obtain the 'optimal' parameters.

Cumulative residual entropy (CREn), initially proposed by us for the task of information measurement and image registration [14], is an alternative measure of uncertainty in a random variable. CREn overcomes some of the issues of Shannon entropy, while still retains many of the important properties of Shannon entropy [14]. Moreover, it offers some very desirable features for signal analysis, i.e.: 1) CREn has consistent definitions in both the continuous and discrete domains; 2) CREn is more robust to noise than Shannon entropy; 3) CREn is always nonnegative; 4) CREn can be easily computed from sample data and these computations asymptotically converge to the true values. In our previous work, CREn was applied to reliability engineering [14], and the cross-CREn was used in image registration and image segmentation, which has shown superior performance over other entropic based measures [14][15]. The above-mentioned properties make the CREn an attractive tool for analyzing biomedical signals, which has not been investigated to the best of our knowledge.

In this paper, we proposed to apply the CREn as a novel and effective feature extraction method to characterize different hand motions from multi-channel SEMG signals. Our experimental results suggest that CREn has the potential to be applied in the control of SEMG-based multifunctional prosthesis.

2. METHODS

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2.1. CREn

CREn is a novel measure of information which is defined based on the cumulative distribution function rather than regular density function of a random variable. For the non-negative random variables, it can be expressed as follows [14][15]:

Let X be a random vector in R^N, we define the CREn of X by

$$\varepsilon(X) = -\int_{R_+^N} P(|X| > \lambda) \log P(|X| > \lambda) d\lambda \quad (1)$$

where $X=(X_1, X_2, \ldots, X_N)$, $\lambda=(\lambda 1,\ldots,\lambda_N)$, and $|X|>\lambda$ means $|X_i|>\lambda_i$ and $R_+^N=(x_i \in R^N; x_i \geq 0)$.

CREn possesses some desirable features, while retaining many of the important properties of Shannon entropy. Here we list some of those that are relevant to the biomedical signal analysis.

***Robustness*:** Let X be a discrete $R.V.$, taking value (x_1, $x_2,\ldots, x_N$), with probabilities $p_1, p_2,\ldots, p_N$

$$p(X = x_i) = p_i \qquad 1 \leq i \leq N \quad (2)$$

X has Shannon entropy: $H(X)=-\sum p_i log p_i$. Let $\overline{Y}_n$ have density f_n and be independent of X. $Z_n = X + \overline{Y}_n$ is no longer discrete, and has a density. Let X be as in (2) and $\overline{Y}_n$ as above. Suppose $\overline{Y}_n \to 0$ in probability. Then

$$h(X + \overline{Y}_n) \to -\infty \quad (3)$$

Note: If we consider $\overline{Y}_n$ as noise in a signal, the essence of this theorem is that $h(X+\overline{Y}_n)$ does not converge to $H(x)$ when $\overline{Y}_n \to 0$. The same situation as in last theorem, we have

$$\lim_{\overline{Y}_n \to 0} \varepsilon(X + \overline{Y}_n) \to \varepsilon(X) \quad (4)$$

for CREn [14].

***Weak Convergence*:** Let the random variables X_k converge in distribution to the random variable X; by this we mean

$$\lim_{k\to\infty} E[\varphi(X_k)] = E[\varphi(X)] \quad (5)$$

for all bounded continuous functions φ on R^N, if all the X_k are bounded in L^p for some $p>N$, then

$$\lim_{k\to\infty} \varepsilon(X_k) = \varepsilon(X) \quad (6)$$

The weak convergence theorem indicates that CREn computed from samples (using histograms) converges to the true value (i.e. their continuous counterpart) unlike the Shannon entropy, where Shannon entropy does not converge to differential entropy when the sample size goes to infinity [14].

For comparison purposes, FEn, SEn and AEn are also adopted in this work. For more details about these entropies, readers can refer to[11], [10]and [6].

2.2. Subjects and Data Acquisition

Ten healthy subjects (age: 22 ± 2 (mean ± SD) years old) participated in the experiment. All subjects were right handed, and none of them had any history of neuromuscular diseases. Each was given the written informed consent prior to the experiment.

Four channel SEMG signals were recorded using the bipolar, Ag-AgCl, surface electrodes (diameter 15 mm, centre spacing 20 mm). 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 [1]. The reference electrode was placed on the proximal head of the ulna. SEMG signals were digitally sampled at 1k Hz with amplified gain of 2000, and filter bandwidth of 10-500 Hz.

Each subject was instructed to perform 6 different hand and wrist motions, namely wrist flexion, wrist extension, radial deviation, ulnar deviation, hand closing and hand opening. Subjects implemented every type of the motions for 60 trials and each contraction trial was held for 5 second. The SEMG data were then recorded once the contraction was established. There is a 2 minute resting period after each motion to avoid muscle fatigue.

2.5. Signal Processing

The SEMG signals were segmented for each trial to calculate the entropy. The segment length was 1s with 1024 points starting from the 2nd second of the recording. For each subject, 30 segments in every type of motions were randomly selected, and a total of 180 segments were grouped as the training set. The remainder segments were then used as the testing set to verify the performance of different entropies.

Features such as CREn, FEn, SEn and AEn are computed for all the SEMG segments, which then were fed to SVM and LDA, respectively. The one-against-one (OAO) method of SVM is adopted for multi-classification in this work [16]. We refer the readers to [16] and [17] for the theories about SVM and LDA.

3. RESULTS

3.1. Qualitative Feature Distribution

For an intuitionistic observation of the feature distributions of 6 known motions, we randomly selected the distributions in channel 2 and channel 3 from one subject 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 6 motions in Fig. 1(c) and 2(d) are not clearly distinguishable. There overlapped points indicate that it is difficult to discriminate 6 motions with SEn and AEn. On the other hand, points distributions in Fig. 1(a) and 2(b) are much clearer with the boundaries and points of different motions much more apparent. Similar distributions are also

observed in all other subjects, which indicate that different motions can be potentially classified with CREn and FEn.

3.2. Classification Accuracy

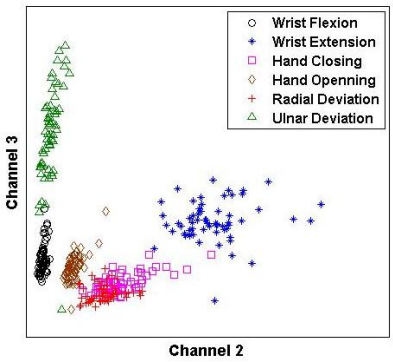
Table 1 and Table 2 show the mean classification accuracies of SVM and LDA for different entropy-based features in all kinds of channel combinations, respectively. For both classification algorithms that we used, it is obvious that the mean classification accuracies of CREn are all much higher than those of other three entropies in almost all kinds of channel combinations. The best mean classification accuracies that are achieved by CREn feature with SVM and LDA are 97.17±1.97% and 93.56±4.13%, respectively, in four channel combination.

TABLE 1 MEAN CLASSIFICATION ACCURACIES OF SVM FOR DIFFERENT FEATURES (UNIT: %)

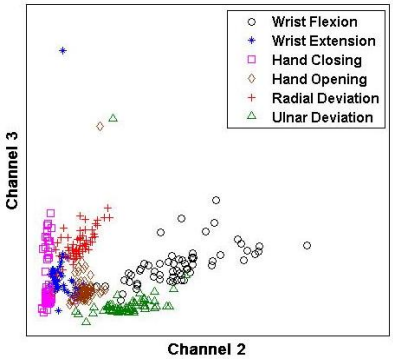
Channel Combination	SVM			
	CREn	FEn	SEn	AEn
1&2	*83.95±6.88*	79.11±9.18	49.39±6.23	36.11±7.31
1&3	*78.89±7.60*	73.34±9.83	44.61±8.36	39.22±9.41
1&4	*83.30±7.81*	76.95±10.87	43.83±4.17	41.39±7.85
2&3	*81.56±8.90*	77.83±11.20	46.78±11.77	33.95±10.40
2&4	*87.39±7.54*	84.78±6.94	46.89±10.13	37.06±9.55
3&4	*81.78±7.99*	76.00±11.81	44.11±9.89	41.28±10.06
1&2&3	*92.56±3.69*	88.89±5.58	57.95±7.88	40.56±10.46
1&2&4	*94.11±3.55*	91.11±5.57	55.11±4.59	47.17±9.15
1&3&4	*91.56±5.64*	87.94±8.28	52.28±8.79	49.17±11.99
2&3&4	*94.67±3.67*	91.39±6.97	56.89±11.29	43.11±13.24
1&2&3&4	***97.17±1.97***	93.67±4.92	64.50±7.18	51.44±11.63

TABLE 2 MEAN CLASSIFICATION ACCURACIES OF LDA FOR DIFFERENT FEATURES (UNIT: %)

Channel Combination	LDA			
	CREn	FEn	SEn	AEn
1&2	*78.17±10.58*	75.00±11.26	47.83±7.77	31.61±7.46
1&3	*72.17±7.60*	69.89±10.90	43.50±7.51	33.06±9.66
1&4	*75.73±10.25*	75.17±9.81	41.22±3.15	34.45±9.01
2&3	*77.89±10.18*	74.78±11.00	49.06±9.69	32.22±10.22
2&4	*82.06±9.94*	79.61±7.25	45.72±8.40	31.56±12.07
3&4	*74.84±10.13*	74.78±10.15	43.56±9.85	37.39±12.52
1&2&3	*87.22±5.64*	84.28±7.08	57.11±9.28	38.94±10.97
1&2&4	*89.28±6.47*	86.56±6.48	54.50±6.65	39.00±11.38
1&3&4	84.67±6.89	*84.83±6.44*	51.67±5.93	42.39±12.61
2&3&4	*89.50±5.39*	88.17±7.67	55.67±10.56	39.39±16.25
1&2&3&4	***93.56±4.13***	90.78±4.90	62.33±8.34	45.50±14.93



(a)



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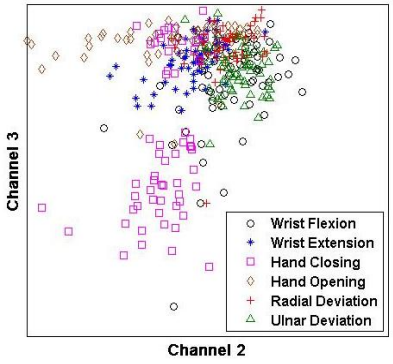
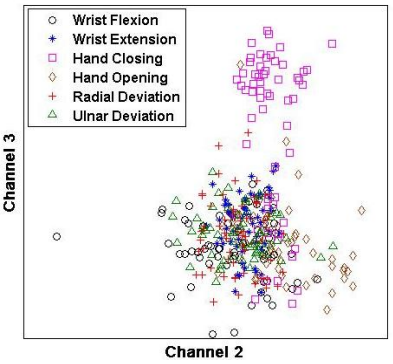


(c)



(d)

Fig. 1 Scatter plot of entropy values of two-channel SEMG signals for six motions. (a) distribution of CREn values; (b) distribution of FEn values; (c) distribution of SEn values; (d) distribution of AEn values

4. DISCUSSION

In this paper, we propose to apply CREn to extract feature from multi-channel SEMG signals for the discrimination of 6 hand and wrist motions. In both SVM and LDA classifiers, almost all the best classification accuracies are all obtained from CREn-based methods in all kinds of channel combination, and the highest accuracy is 97.17±1.97% with the combination of CREn and SVM.

Muscle contraction in different movements will generate different regular EMG signals, which can be used as a characteristic feature of EMG signals for different motions. CREn can well track the qualitative changes in time series patterns. Therefore, the temporal regularity of SEMG time series then can be well assessed by CREn. As shown in Table 1 to Table 2, CREn-based feature obtained highest classification accuracies in both two classifiers in all channel combinations comparing with FEn, SEn and AEn, which proves its efficiency to characterize SEMG signals.

Another important advantage of CREn is that its computational complexity is very low, because there is only one parameter to be set in the computation of CREn. While in FEn, SEn and AEn, the number of free parameters to be set are 3, 2 and 2, respectively. Therefore, the one parameter of CREn is much easier to be set than those of other entropies. The low computational complexity and powerful characterization of SEMG make it possible for CREn to be used as a feature extraction method in the real-time prosthetic control, which will be further studied in our further work. Moreover, we will study the feasibility of CREn in analyzing other biomedical signals.

5. CONCLUSION

In conclusion, we proposed to use CREn as an effective feature extraction method in the classification of different hand and wrist motions with multi-channel SEMG signal. The results indicate that CREn-based classification outperforms all other entropy-based methods compared in this study both by the SVM and LDA to discriminate six hand and wrist motions. Moreover, the computational complexity of CREn is lower than those of other entropies compared. It suggests that the CREn has the potential to be used as the feature for the control of SEMG-based multifunctional prosthesis.

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