Characterization of Surface EMG Signal Based on Fuzzy Entropy

Weiting Chen, Zhizhong Wang, Hongbo Xie, and Wangxin Yu

***Abstract*—Fuzzy entropy (FuzzyEn), a new measure of time series regularity, was proposed and applied to the characterization of surface electromyography (EMG) signals. Similar to the two existing related measures ApEn and SampEn, FuzzyEn is the negative natural logarithm of the conditional probability that two vectors similar for m points remain similar for the next $m+1$ points. Importing the concept of fuzzy sets, vectors' similarity is fuzzily defined in FuzzyEn on the basis of exponential function and their shapes. Besides possessing the good properties of SampEn superior to ApEn, FuzzyEn also succeeds in giving the entropy definition in the case of small parameters. Its performance on characterizing surface EMG signals, as well as independent, identically distributed (i.i.d.) random numbers and periodical sinusoidal signals, shows that FuzzyEn can more efficiently measure the regularity of time series. The method introduced here can also be applied to other noisy physiological signals with relatively short datasets.**

***Index Terms*—ApEn, electromyography (EMG), FuzzyEn, regularity, SampEn.**

I. Introduction

SURFACE electromyography (EMG) signal has been widely used in rehabilitation, prosthesis control, muscle fatigue analysis, and clinical diagnosis, owing to its convenient and noninvasive access to the study of myoelectric features of neuromuscular activation [1]–[4]. The recognition of the signal can be mainly summarized in two steps: feature extraction and feature classification, with the former being of the main kernel in system recognition [5]. However, the surface EMG signal is extremely complex as it is influenced by many factors in the electrophysiology and the recording environment [2]. The complexity of the signal poses a great challenge to its feature extraction.

The present methods used in EMG feature extraction are most commonly based on the assumption that the signal is linear. However, it has been recently recognized that EMG signal exhibits nonlinearity [6], [7], and can hardly be described by simple linear models. Therefore, methods of nonlinear time series analysis have been introduced to EMG to get a better insight into the complex signal [6], [8]–[16]. Efforts have been made to use fractal dimension to quantify motor unit recruitment patterns [6]; evaluate human muscle's potential in athletics [8], study the relation between the activity of the biceps brachii and the fractal dimension of EMG during flexion–extension of the forearm [9], characterize action EMG [10], and so on. Average maximum finite-time Lyapunov exponents were estimated to quantify the local dynamic stability of human walking kinematics [11]. Other studies applied recurrence quantification analysis to the evaluation of muscle fatigue [12], [13]. Efforts have also been made to analyze EMG by combining several parameters such as correlation dimension, Lyapunov spectrum, Kaplan–Yorke dimension, and the recurrence plots in testing the nonlinearity, stationarity, and determinism of EMG signals from muscles in the leg during walking and maximum voluntary contraction [14], in comparing various postures or muscle contraction conditions [15], in evaluating the level of muscular efforts under static work conditions [16], etc.

Most nonlinear dynamic measures, however, usually need very large dataset to get reliable and convergent values in their calculation [17], and may lead to spurious results when applied to short or irregular sequences of real experimental data [18]. When dealing with surface EMG, another problem is the unavoidable noises. To solve the problems of short data and noisy recordings in physiological signals, Pincus [19]–[21] developed approximate entropy (ApEn) to measure the system complexity, which is applicable to noisy and short dataset. Superior to most nonlinear dynamic measures such as fractal dimension [20], [22], Lyapunov spectrum, Kolmogorov–Sinai (KS) entropy [20], and spectral entropy [23], ApEn has shown potential application to a wide range of physiological and clinical signals such as hormone pulsatility, genetic sequences, respiratory patterns, heart rate variability, electrocardiogram, and electroencephalography [24]–[30]. In the study of EMG signal, Radhakrishnan *et al.* [31] chose ApEn as the discriminating statistic for their tests for possible nonlinearity of the contraction segments interspersed in a uterine electromyography. Meng *et al.* [32] made a comprehensive nonlinear analysis by calculating ApEn together with other nonlinear measures to test whether EMG is nonlinear deterministic or random. Vaillancourt and Newell [33] used cross-ApEn to assess the time-dependent structure between the limb acceleration and EMG activity. Nevertheless, ApEn suggests more similarity than is present and is thus biased. To be free of the bias caused by self-matching, Richman and Moorman [34] developed another related measure of time series regularity named sample entropy (SampEn). Despite its advantage of being less dependent on dataset length and the relative consistency over a broader range of m, r, and N values, SampEn(m, r, N) is not defined if no template and forward match occurs in the case of small N and r [34].

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In this work, we proposed another related measure of time series regularity, fuzzy entropy (FuzzyEn), and applied it to characterizing surface EMG signals. The rest of the paper is organized as follows. Section II introduces the new measure, fuzzy entropy based on fuzzy sets. Section III first tests the method on independent, identically distributed (i.i.d.) uniform random numbers and periodical signals, and then applies it to the characterization of experimental surface EMG signals. Features are also extracted from the signals using ApEn [35] and SampEn [36] to make a comparison of the three related measures with regard to their performance on measuring signal regularity. Finally, Section IV concludes the paper.

II. Methods

In the two existing related regularity measures ApEn and SampEn, similarity of vectors is based on Heaviside function, which can be represented as

$$\theta(z) = \begin{cases} 1, & \text{if } z \geq 0 \\ 0, & \text{if } z < 0. \end{cases} \tag{1}$$

Heaviside function leads to a kind of conventional two-state classifier, where an input pattern is judged its belongingness to a given class by whether it satisfies certain precise properties required of membership. In the real physical world, however, boundaries between classes may be ambiguous, and it is difficult to determine whether an input pattern belongs totally to a class. The concept of "fuzzy sets" introduced by Zadeh [37] in 1965 puts forward a means of characterizing such input–output relations in an environment of imprecision. By introducing the "membership degree" with a fuzzy function $\mu_C(x)$ which associates each point x with a real number in the range [0, 1], Zadeh's theory provided a mechanism for measuring the degree to which a pattern belongs to a given class: the nearer the value of $\mu_C(x)$ to unity, the higher the membership grade of x in the set ***C***. In FuzzyEn, we imported the concept and employed the family of exponential functions $\exp(-(d_{\mathrm{ij}}^m)^n/r)$ as the fuzzy function to get a fuzzy measurement of two vectors' similarity based on their shapes. The family of exponential function possesses the following desired properties: 1) being continuous so that the similarity does not change abruptly; 2) being convex so that self-similarity is the maximum.

A. Definition of FuzzyEn

For an N sample time series $\{u(i) : 1 \leq i \leq N\}$, given m, form vector sequences $\{\mathbf{X}_i^m, i = 1, \ldots, N-m+1\}$ as follows:

$$\mathbf{X}_i^m = \{u(i), u(i+1), \ldots, u(i+m-1)\} - u0(i), \tag{2}$$

here $\mathbf{X}_i^m$ represents m consecutive u values, commencing with the ith point and generalized by removing a baseline

$$u0(i) = \frac{1}{m}\sum_{j=0}^{m-1} u(i+j). \tag{3}$$

For certain vector $\mathbf{X}_i^m$, define the distance d_{ij}^m between $\mathbf{X}_i^m$ and $\mathbf{X}_j^m$ as the maximum absolute difference of the corresponding scalar components

$$\begin{aligned} d_{ij}^m &= d\left[\mathbf{X}_i^m, \mathbf{X}_j^m\right] \\ &= \max_{k \in (0, m-1)} |(u(i+k) - u0(i)) \\ &\quad - (u(j+k) - u0(j))|. \end{aligned} \tag{4}$$

Given n and r, calculate the similarity degree D_{ij}^m of $\mathbf{X}_j^m$ to $\mathbf{X}_i^m$ through a fuzzy function $\mu(d_{ij}^m, n, r)$

$$D_{ij}^m(n,r) = \mu\left(d_{ij}^m, n, r\right) \tag{5}$$

where the fuzzy function $\mu(d_{ij}^m, n, r)$ is the exponential function

$$\mu\left(d_{ij}^m, n, r\right) = \exp\left(-\left(d_{ij}^m\right)^n / r\right). \tag{6}$$

Define the function ϕ^m as

$$\phi^m(n,r) = \frac{1}{N-m}\sum_{i=1}^{N-m}\left(\frac{1}{N-m-1}\sum_{j=1, j\neq i}^{N-m} D_{ij}^m\right). \tag{7}$$

Similarly, form $\{\mathbf{X}_i^{m+1}\}$ and get the function ϕ^{m+1}

$$\begin{aligned} \phi^{m+1}(n,r) &= \frac{1}{N-m} \\ &\quad \times \sum_{i=1}^{N-m}\left(\frac{1}{N-m-1}\sum_{j=1, j\neq i}^{N-m} D_{ij}^{m+1}\right). \end{aligned} \tag{8}$$

Finally, we can define the parameter FuzzyEn(m, n, r) of the sequence as the negative natural logarithm of the deviation of ϕ^m from ϕ^{m+1}

$$\begin{aligned} &\mathrm{FuzzyEn}(m,n,r) \\ &\quad = \lim_{N\to\infty}[\ln \phi^m(n,r) - \ln \phi^{m+1}(n,r)] \end{aligned} \tag{9}$$

which, for finite datasets, can be estimated by the statistic

$$\mathrm{FuzzyEn}(m,n,r,N) = \ln \phi^m(n,r) - \ln \phi^{m+1}(n,r). \tag{10}$$

B. Parameter Choices of FuzzyEn

There are three parameters that must be fixed for each calculation of FuzzyEn. The first parameter m, as in ApEn and SampEn, is the length of sequences to be compared. The other two parameters r and n determine the width and the gradient of the boundary of the exponential function respectively. Typically [20], larger m allows more detailed reconstruction of the dynamic process. But a too large m value is unfavorable due to the need of a very large N (10^m–30^m), which is hard to meet for a physiological dataset, or the need of a very broad boundary, which will lead to information loss. As to the fuzzy similarity boundary determined by the other two parameters r and n, too

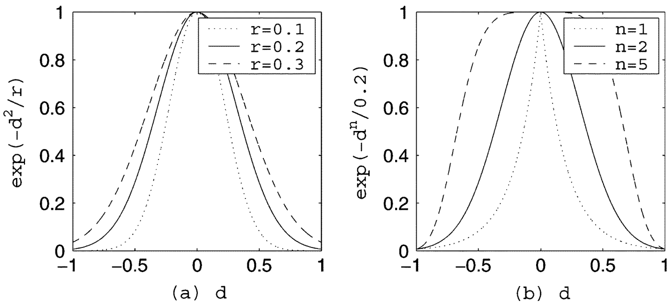

Fig. 1. An illustration of the exponential function $(\exp(-d^n/r))$ with different parameter choices. (a) Exponential function with fixed $n = 2$ and varied r (0.1, 0.2, and 0.3). (b) Exponential function with fixed $r = 0.2$ and varied n (1, 2, and 5).

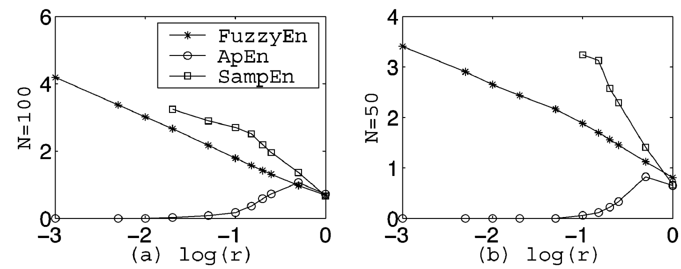

Fig. 2. FuzzyEn$(2, 2, r, N)$, ApEn$(2, r, N)$, and SampEn$(2, r, N)$ as functions of r for i.i.d. uniform random numbers. SampEn gives no entropy values when r is smaller than 0.05 for $N = 100$, and 0.1 for $N = 50$. Problem does not embarrass ApEn and FuzzyEn.

narrow ones will result in salient influence from noise, while too broad a boundary, as mentioned above, is supposed to be avoided for fear of information loss. Fig. 1 illustrates the effect of different parameter choices of r and n on the exponential function. Experimentally, it is convenient to set the width of the boundary as r multiplied by the standard deviation (SD) of the original dataset [34] and choose small integers for the n selection.

Another parameter is sampling rate, which should be higher than the Nyquist rate. However, too high a sampling rate is not necessary and will increase computational load.

III. Experimental Results

To illustrate the performance of the new regularity measure compared with the two existing ones, in this section we firstly tested its performance on i.i.d. uniform random numbers and periodical sinusoidal signals, and then applied the three measures to the characterization of experimental surface EMG signals. The parameter r in this section refers to the multiplicand in r^*SD.

A. Performance on i.i.d. Uniform Random Numbers and Periodical Sinusoidal Signals

The three statistics of FuzzyEn, ApEn, and SampEn were firstly tested on i.i.d. uniform random numbers. Fig. 2 shows the performance of FuzzyEn(2,2, r, N), ApEn(2, r, N), and SampEn(2, r, N) on i.i.d. random numbers with different lengths of N =100 and $N = 50$. SampEn gives no entropy values when r is smaller than 0.05 for $N = 100$ in Fig. 2(a), and 0.1 for $N = 50$ in Fig. 2(b). So the calculation of SampEn is confronted with the problem of parameter limitation, and the shorter the dataset is, the larger the minimum tolerance r is needed. But the problem does not embarrass the calculation of ApEn and FuzzyEn.

The performances of the three statistics of FuzzyEn, ApEn, and SampEn were also tested on two periodical sinusoidal signals at different frequencies 50 and 100 Hz (see Fig. 3). For both N =50 and $N = 500$, FuzzyEn entropy values of the sinusoidal signal at 100 Hz are higher than those of the sinusoidal signal at 50 Hz for all r values, which indicates strong relative consistency of its regularity measurement. Values of ApEn for the two signals, however, may tilt over with each other no matter whether $N = 50$ or $N = 500$, which indicates poor consistency. Though SampEn shows good relative consistency when measuring the regularity of the two sinusoidal signals with enough data points [$N = 500$ in Fig. 3(f)], it no longer holds the property when dealing with the same two signals with short data length [$N = 50$ in Fig. 3(e)].

B. Performance on Experimental Surface EMG Signals

1) Materials: 160 sets of two-channel surface EMG signals were analyzed for four different motions: hand grasping (HG), hand opening (HO), forearm supination (FS), and forearm pronation (FP). The signal collection was completed in the EMG room of Shanghai Huashan Hospital, Shanghai, China, with informed consents provided by all the subjects. Skin surface of interested area was abraded with alcohol beforehand, and two sets of discs bipolar Ag/AgCl electrodes with diameters of 5 mm were placed over the flexor carpi radialis and the extensor carpi radialis longus on the right forearm. The sample rate was set to 1000 Hz and the bandwidth of the amplifier-filter was 10–500 Hz, for surface EMG is believed to contain relevant information only up to about 500 Hz, with the dominant energy in the range of 50–150 Hz [38]. Fig. 4 describes 2.5 s waveform of surface EMG during forearm pronation.

2) Parameter Selections: For the selection of parameters in FuzzyEn(m, n, r, N), ApEn(m, r, N), and SampEn(m, r, N) in our experiments concerning surface EMG signals, m was fixed to 2 in that surface EMG signals recorded during HG, HO, FP, and FS actions are usually short, and the other parameters, r and n, were chosen on the basis of experimental data. We calculated the entropy values for 20 sets of surface EMG signals of forearm pronation with different r (for all the three entropy definitions) and n (for FuzzyEn only) values, and then evaluated the SD of the entropy values. The effect of different parameter selections on the entropy values is demonstrated in Fig. 5. Generally, the larger the r and n are, the smaller the SD is. But as mentioned above, too wide a boundary will lead to information loss. Therefore, appropriate selections of r and n can be picked at the point where the decrease in SD becomes slow. In Fig. 5, we can see that SDs of FuzzyEn and SampEn decrease smoothly with the increasing r, whereas SD of ApEn may jump up and down when r increases, which indicates that the former two entropy statistics have better relative consistency than the latter one. We can also find that the SD of FuzzyEn is smaller

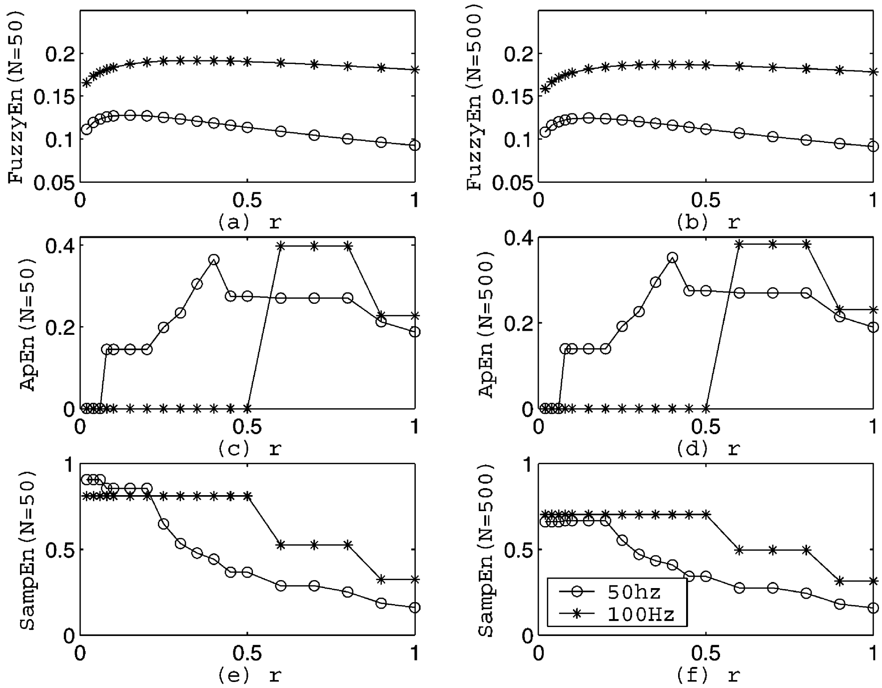

Fig. 3. FuzzyEn$(2, 2, r, N)$, ApEn$(2, r, N)$, and SampEn$(2, r, N)$ as functions of r for two sinusoidal signals at different frequencies 50 and 100 Hz. For both $N = 50$ and $N = 500$, FuzzyEn values for the sinusoidal signal at 100 Hz are higher than those of the signal at 50 Hz for all the r values, whereas ApEn values for the two signals tilt over with each other when r decreases. SampEn shows relative consistency when measuring the regularity of the two signals for (f) $N = 500$, but it no longer holds the property when dealing with the same two signals with small data points of (e) $N = 50$.

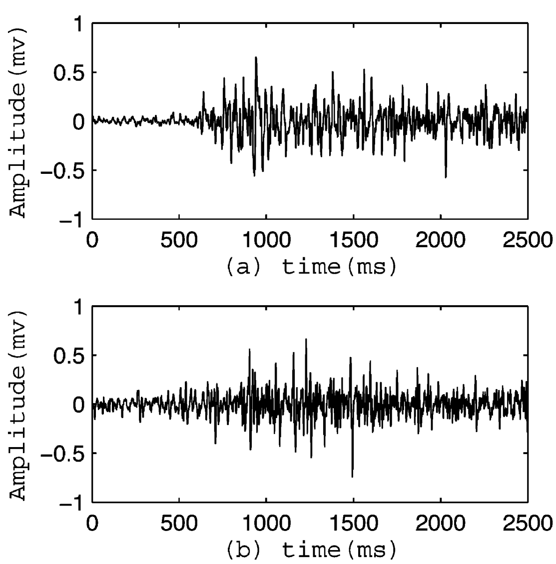

Fig. 4. 2.5s waveform of surface EMG during forearm pronation. The abscissa is time (ms), and the ordinate is the amplitude (mv). The two channels of surface EMG signals sampled at 1000 Hz were recorded from (a) the flexor carpi radialis and (b) the extensor carpi radialis longus on the right forearm.

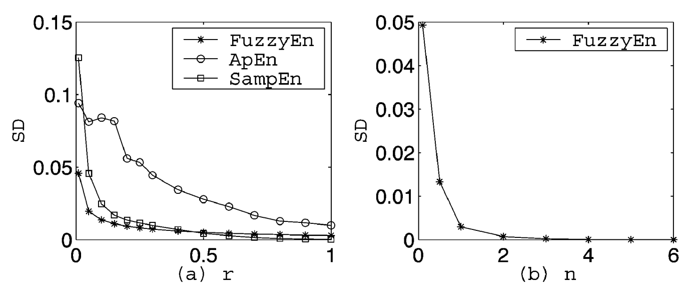

Fig. 5. Effect of different parameter selections on FuzzyEn, ApEn, and SampEn for surface EMG signals. SDs of entropy values for twenty sets of surface EMG signals during forearm pronation action are shown in (a) as functions of r (for all the three entropy measurements) and in (b) as a function of n (for FuzzyEn only). Generally, SD decreases when r and n increase.

than those of ApEn and SampEn, which implies that FuzzyEn is more stable than the other two measures.

In this study, $n = 2$ was chosen in the calculation of FuzzyEn(m, n, r, N) because SD changes little with $n > 2$; and $r = 0.3$ was set for the calculation of FuzzyEn and SampEn, in that the increase in r has little influence on the decrease in SDs of the two statistics with $r > 0.3$; for the calculation of the statistics of ApEn, r was also set to 0.3 for the sake of convenience.

3) Results: SDs of the three entropy statistics for all the two-channel surface EMG signals during the four motions (FP, FS, HG, and HO) are listed in Table I. Among the three statistics, FuzzyEn has the smallest SD, SampEn comes next, and ApEn has the largest SD. Figs. 6–8 further depict the performances of FuzzyEn, ApEn, and SampEn on characterizing surface EMG signals of the four known actions. The abscissa in each figure represents the corresponding entropy value of the surface EMG from channel 1, and the ordinate refers to that from channel 2. In Fig. 7, points of the four motions from ApEn are not clearly distinguishable, with the boundaries of FP, HG, and HO somewhat overlapping each other. Although points of FS are seen apart from those of the other three motions, 40 points fall into two regions rather than into one. SampEn (in Fig. 8) shows

TABLE I
STANDARD DEVIATIONS OF THE THREE ENTROPIES FOR THE TWO-CHANNEL SURFACE EMG SIGNALS DURING THE FOUR MOTIONS (FP, FS, HG, AND HO)

	Standard Deviation					
	Channel 1			Channel 2		
	FuzzyEn	ApEn	SampEn	FuzzyEn	ApEn	SampEn
FP	0.0025	0.0483	0.0256	0.0038	0.0780	0.0269
FS	0.0027	0.0655	0.0169	0.0005	0.1434	0.0165
HG	0.0047	0.0518	0.0504	0.0087	0.0876	0.0481
HO	0.0039	0.0472	0.0285	0.0029	0.0679	0.0195

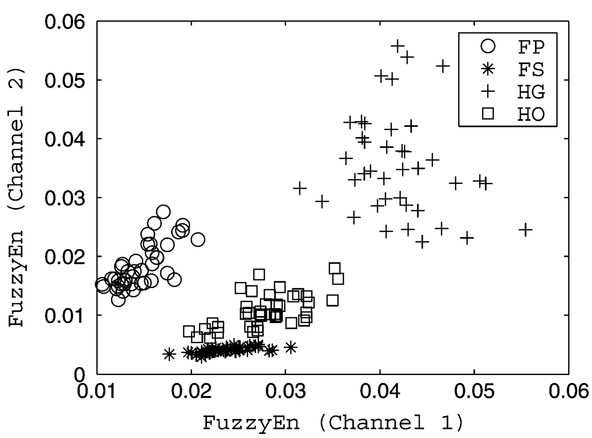

Fig. 6. Scatter plot of FuzzyEn entropy values of two-channel surface EMG signals for the four different motions. The abscissa represents the FuzzyEn entropy value of the surface EMG from channel 1, and the ordinate refers to that from channel 2. Points of the FuzzyEn entropy values for the four motions fall into four regions and can be distinguished manually.

better distinguishing result than ApEn, with the boundaries between points of different motions much more apparent. However, the seven points of FS are away from the other points of the same motion. On the contrary, they are much closer to those of the other two motions FP and HO. Among the three measures, FuzzyEn owns the best characterizing result. In Fig. 6, all the points of the four motions can be totally distinguished manually.

IV. Discussion and Conclusion

Despite the sacrifice of precisely characterizing the underlying dynamics, FuzzyEn is applicable to relatively short physiological signals by using a small embedding dimension m. In addition, it employs coarse tolerance through the selection of parameters n and r, and thus achieves its robustness to noise. Like ApEn and SampEn, FuzzyEn is the negative natural logarithm of the conditional probability that a dataset of length N, having repeated itself for m points within a boundary, will also repeat itself for $m + 1$ points. It adopts the modifications in which SampEn differs from ApEn: 1) excluding self-matches, i.e., vectors are not compared to themselves; 2) considering only the first $N - m$ vectors of length m so that, for $i \leq N - m$, both $\mathbf{X}_i^m$ and $\mathbf{X}_i^{m+1}$ are defined. By doing so, FuzzyEn gets the good properties that SampEn possesses: more independence on data length and relative consistency which may fail ApEn under certain circumstances.

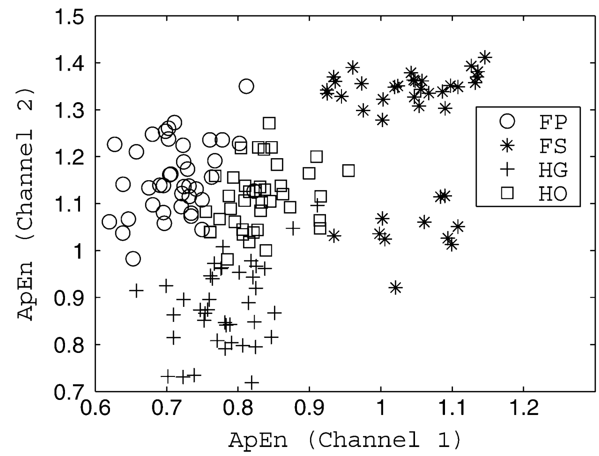

Fig. 7. Scatter plot of ApEn entropy values of surface EMG signals for the four different motions. The abscissa represents the ApEn entropy value of the surface EMG from channel 1, and the ordinate refers to that from channel 2. The boundaries between points of FP, HG and HO somewhat overlap each other. Moreover, the points of FS motion fall into two regions.

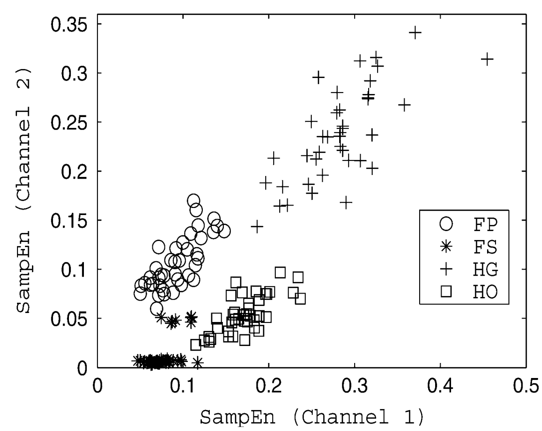

Fig. 8. Scatter plot of SampEn entropy values of surface EMG signals for the four different motions. The abscissa represents the SampEn entropy value of the surface EMG from channel 1, and the ordinate refers to that from channel 2. Different motions are better distinguished than those in Fig. 7. However, the seven points of FS motion are away from the other points of the same motion. On the contrary, they are much closer to the points of the other two motions FP and HO.

Unlike ApEn and SampEn, where the similarity of two vectors is based on Heaviside function, FuzzyEn employs exponential function to bound two vectors' similarity. In a Heaviside function, the boundary is rigid: the contributions of all the data points inside it are treated equally, whereas the data points just outside it are left out. The hard boundary causes discontinuity, which may lead to abrupt changes of entropy values when the tolerance r changes slightly, and even to the failure in SampEn definition if no template-match can be found for small tolerance r. In an exponential function, on the contrary, there is no rigid boundary. The exponential function value around certain vector $\mathbf{X}_i$ can be viewed as the fuzzy membership to indicate the similarity between it and its neighbor $\mathbf{X}_j$. The closer the neighboring vector $\mathbf{X}_j$ is, the more similar $\mathbf{X}_j$ is to $\mathbf{X}_i$, and the similarity between $\mathbf{X}_i$ and $\mathbf{X}_j$ is almost zero when $\mathbf{X}_j$ is far away from $\mathbf{X}_i$. As all the data points are considered as members of exponential function fuzzily, entropy values of FuzzyEn will change continuously and gracefully, and there's no definition limitation of parameters. The exponential function is an ad hoc choice due to its easiness to be understood. Indeed, any other function that possesses the good properties listed in Section II can also be chosen.

Another difference between FuzzyEn and ApEn or SampEn is the construction of m-dimensional vector from one dimensional time series. In both ApEn and SampEn, vectors $\{\mathbf{X}_i^m, i = 1, \ldots, N-m+1\}$ are formed directly from the original m consecutive u values as

$$\mathbf{X}_i^m = \{u(i), u(i+1), \ldots, u(i+m-1)\} \tag{11}$$

and the distance d_{ij}^m between $\mathbf{X}_i^m$ and $\mathbf{X}_j^m$ is defined as

$$d_{ij}^m = d[\mathbf{X}_i^m, \mathbf{X}_j^m] = \max_{k\in(0,m-1)} |u(i+k) - u(j+k)|. \tag{12}$$

Under the definition, $\mathbf{X}_i^m$ and $\mathbf{X}_j^m$ are considered to be similar only when $\max_{k\in(0,m-1)} |u(i+k) - u(j+k)| \leq r$. So vectors' similarity is totally determined by their absolute coordinates, which may fail in the application to those signals with mild fluctuations [29]. In FuzzyEn, the vector sequences are generalized by removing the baseline using (2). In this way, vectors' similarity, determined by the distance d_{ij}^m between the vectors as in (5), depends on their shapes rather than their absolute coordinates, which makes the similarity definition fuzzier.

Regularity of EMG signals varies when muscles are involved in different movements, and can thus be used as a characteristic feature of EMG signals for different motions. Entropy definitions of ApEn, SampEn, and FuzzyEn can track qualitative changes in time series patterns and allow one to assess the temporal regularity of the time series. The better distinguishing result of the four motions by FuzzyEn, compared with those by ApEn and SampEn, demonstrates that the new measure can characterize surface EMG signals more efficiently.

FuzzyEn can also be applied to other physiological signals with short data length in noisy background. Nevertheless, FuzzyEn gives only a single index for the general behavior of a time series. To obtain more sufficient insight into the underlying dynamics, future works can concentrate on multiscale FuzzyEn entropy analyses through characterizing time series at different time scales. Moreover, the parameter selection introduced here is somewhat subjective. Efforts are still needed to give detailed guidelines for the parameter optimization in FuzzyEn calculation.

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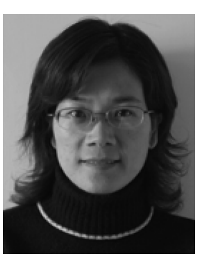

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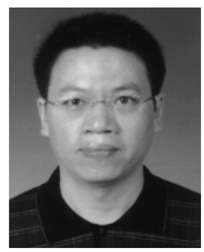

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