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Automatic EMG Feature Evaluation for Controlling a Prosthetic Hand Using a Supervised Feature Mining Method: An Intelligent Approach

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Abstract

Electromyograph (EMG) has the properties of large variations and nonstationarity. There are two issues in the classification of EMG signals. One is the feature selection, and the other is the classifier design. Subject to the first issue, we propose a supervised feature mining (SFM) method, which is an intelligent approach based on genetic algorithms (GAs), fuzzy measure, and domain knowledge on pattern recognition. The SFM can find the optimal EMG feature subset automatically and remove the redundant from a large amount of feature candidates without taking trial-and-error. In the experiments, all feature candidates and optimal feature subset are conducted to demonstrate the validity of the proposed SFM. Moreover, experimental results show that the optimal EMG feature subset obtained from SFM can obtain higher classification rates compared with using all feature candidates by *K*-NN method.

Keywords: EMG classification, feature mining, genetic algorithms (GAs), fuzzy measure, self-organizing map.

1. Introduction

EMG classification is one of the most difficult pattern recognition problems because there usually exist large variations in EMG features. Especially, it is difficult to extract useful features from the residual muscles of an amputee. So far, many researches proposed many kinds of EMG features to classify postures and they showed good performance [4][10][18][20][2][6]. However, how to select a feature subset with the best discrimination ability from those features is still an issue for classifying EMG signals. Hence, in this paper, we propose a supervised feature mining method (SFM) to deal with the problem.

In SFM, the intraclass and interclass ambiguities are measured by fuzzy entropy and index of fuzziness in multi-dimensional feature space. Then, a fuzzy feature evaluation index (FFEI) is developed to give an overall measurement of separation and compactness of the class structure in the feature space. The central concept of the proposed SFM is to change the class structure in the feature space according to the relative importance of features. By introducing a set of weighting factors to each feature, the class structure (i.e., the index FFEI) becomes a function of these factors in feature space. A weighting factor implies the relative importance of a feature. Hence, the genetic algorithm (GA) is performed to search the optimal weighting factor automatically. We can select the optimal feature subset according to the weighting factors. The larger the value of the weighting factor is, the more important the feature is.

In this paper, we select eight kinds of different features that have been widely used to classify EMG signals as the feature candidates. They are integral of EMG (IEMG) [10], waveform length (WL) [10], variance (VAR) [16][20], zero crossing (ZC) [10][20], slope sign changes (SSC) [10], Willison amplitude (WAMP) [18], autoregressive model (ARM) [18][6] and histogram of EMG (HEMG) [18], respectively. Accordingly, we select eight kinds of frequently used prehensile postures to be classified. SFM can select optimal feature subset from these feature candidates automatically without taking trial-and-error. The process will be performed on PC-based processes (off-line).

The rest of this paper is organized as follows. Section 2 illustrates the equipment for the EMG acquisition. Furthermore, eight postures to be classified are selected. In the later of this section, seven kinds of selected features candidates will be introduced. In Section 3, the detail of the proposed supervised feature mining method, SFM, is illustrated. Section 4 introduces the EMG classification briefly. Several experiments will be conducted in Section 5. Finally, we have some conclusion remarks in Section 6.

2. EMG Feature Candidates and Extractions

Eight types of prehensile postures to be classified are selected in that they are typical postures of most frequent use for human beings. The eight postures are power grasp (PG), hook grasp (HG), wrist flexion (WF), lateral pinch (LP), flattened hand (FH), centralized grip (CEG), three-jaw chuck (TJC), and Cylindrical grasp (CYG), and they are listed in Table 1.

Table 1 Eight kinds of prehensile postures to be classified

Posture types	Power grasp	Hook grasp	Wrist flexion	Lateral pinch
Posture graphics				
Posture types	Flattened hand	Centralized grip	Three-jaw chuck	Cylindrical grasp
Posture graphics				

In order to obtain meaningful EMG signals for eight kinds of prehensile postures, the placement of EMG surface electrodes is important. According to the relations between the muscle location and the prehensile postures [12], the three EMG surface electrodes are placed on palmaris longus, extensor digitorum and flexor carpi ulnaris and therefore three channels are used (see Fig. 1).

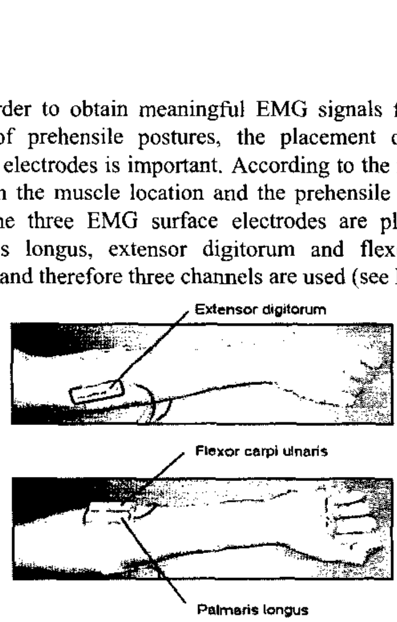

Fig. 1. The placements of EMG surface electrodes

The eight postures generate different EMG signals with various characteristics. In this paper, seven kinds of features to be evaluated are selected as follows.

A. Integral of EMG (IEMG)

IEMG is an estimate of the summation of absolute value of the EMG signal. It is given by

$$IEMG = \frac{1}{N}\sum_{k=1}^{N} |emg_k| \qquad (1)$$

where emg_k is the k_{th} sample data out of N samples of EMG raw data.

B. Waveform Length (WL)

WL is a cumulative variation of the EMG that can indicate the degree of variation about the EMG signal. It is given by

$$WL = \sum_{k=1}^{N-1} | emg_{k+1} - emg_k | \qquad (2)$$

C. Variance (VAR)

VAR is a measure of the power density of the EMG signal as given by

$$VAR = \frac{1}{N-1}\sum_{k=1}^{N} emg_k^2 \qquad (3)$$

D. Zero Crossing (ZC)

ZC counts the number of times that the signal crosses zero. A threshold needs to be introduced to reduce the noise induced at zero crossing. Given two contiguous EMG signals emg_k and emg_{k+1}, the ZC can be calculated as

$$ZC = \sum_{k=1}^{N-1} \left[\mathrm{sgn}(-emg_k \times emg_{k+1}) \cap |emg_k - emg_{k+1}| \geq 0.02 \right] \qquad (4)$$

$$\text{where} \quad \mathrm{sgn}(x) = \begin{cases} 1, & \text{if } x > 0 \\ 0, & \text{otherwise} \end{cases} \qquad (5)$$

E. Slope Sign Changes (SSC)

SSC counts the number of times the slope of the signal changes sign. Similarly, it needs to include a threshold to reduce the effect of noise induced by slope sign changes. Given three contiguous EMG signals emg_{k-1}, emg_k and emg_{k+1}, the number of slope sign changes increases if

$$\begin{aligned} &(emg_k - emg_{k-1}) \times (emg_k - emg_{k+1}) \geq 0.03 \\ &\text{for } k = 2, \ldots, N-1 \end{aligned} \qquad (6)$$

F. Willison Amplitude (WAMP)

WAMP is the number of counts for each change of the EMG signal amplitude that exceeds a defined threshold. It can indicate the muscle contraction level as given by

$$\begin{aligned} &WAMP = \sum_{k=1}^{N-1} f(|emg_k - emg_{k+1}|) \\ &\text{where} \quad f(x) = \begin{cases} 1, & \text{if } x > 0.3 \\ 0, & \text{otherwise} \end{cases} \end{aligned} \qquad (7)$$

G. Autoregressive Model (ARM)

It is difficult to analyze the EMG signal because of its nature of nonlinearity and nonstationarity. However, in a short time period the EMG signal can be regarded as a stationary Gaussian process and can be represented by an autoregressive model (ARM). ARM is used to identify the EMG time series as

$$y_k = -\sum_{i=1}^{M} a_i emg_{k-i} + w_k \qquad (8)$$

where y_k is the kth output of ARM and emg_{k-i} is the $(k-i)$th sample data out of N samples of EMG raw data. M is the order of ARM, a_i are the estimate of the ARM parameters and w_k is the white noise. The ARM parameters a_i can be calculated via the adaptive least mean square (LMS) method and thus we have

$$a_i(n+1) = a_i(n) - 2\beta e(n) emg(n-i) \qquad \text{for } i = 1 \ldots M \quad (9)$$

where $a_i(n)$ is the original ARM parameter, β is a constant rate of convergence and $e(n)$ is the difference between the nth sample data of EMG raw data and the nth output of ARM. Hence, we can update the new ARM parameter by Eqn.(9). A model order of 4 is adequate for AR time series modeling of EMG signal. Thus, an ARM contains four feature components. The simulation of the original EMG signal using a fourth-order AR model is shown in Fig. 2.

H. Histogram of EMG (HEMG)

HEMG is the extension of the ZC and WAMP. It counts how many samples in the particular voltage range and provides the information about the frequency which the EMG signals reach multiple amplitude levels. Similar to the setting in [18], the voltage range [-10, +10] is divided into nine equivalent intervals and the counts in each voltage interval will be multiplied by 0.01. A HEMG contains nine feature components.

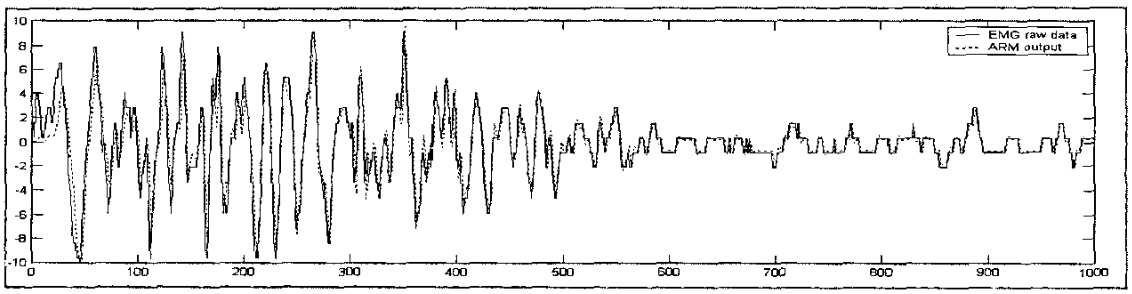

Fig. 2. The simulation of the original EMG signal using a fourth-order AR model

3. Supervised Features Mining (SFM)

In this section, we introduce the proposed supervised feature mining (SFM) for EMG features in details.

3.1 Compactness index

Suppose that there are l classes ($C_1,...,C_k,...,C_l$) to be classified, and each class has p patterns. The feature space is an n-dimensional feature space $F=(F_1,...,F_n)$. The distance between a pattern $F_j \in C_k$ and its corresponding mean in class C_k is defined as the normalized Euclidean distance

$$d_k(F_j)=\left[\sum_{i=1}^{n}\left(\frac{|F_{ij}-m_{ki}|}{\alpha_{ki}}\right)^2\right]^{1/2}, \quad F \in C_k \qquad (10)$$

where

$$\alpha_{ki}=N_1 \cdot \max_j |F_{ij}-m_{ki}|, \quad F_i \in C_k \qquad (11)$$

Note that m_{ki} denotes the mean of class C_k along the ith feature axis, and α_{ki} is a normalization factor, in which N_1 is a positive number so that the value of $d_k(F_j)$ would lie in the interval [0, 0.5], and p is the class size. Since the normalized Euclidean distance for a pattern $F_j \in C_k$ to the mean has been defined, one can use the $semi-\pi$ membership function to compute the intraclass ambiguity using the fuzzy entropy [17]

$$H_k=\frac{2}{p\ln 2}\sum_{j=1}^{p}S_p(\mu_{semi-\pi}(d_k(F_j))), \quad F_j \in C_k \qquad (12)$$

where $S_p(\bullet)$ is the Shannon function and can be expressed as

$$S_p(\mu(x))=-\mu(x)\ln\mu(x)-(1-\mu(x))\ln(1-\mu(x)) \qquad (13)$$

The multi-dimensional $semi-\pi$ membership function is defined as

$$\mu_{semi-\pi}(x)=\begin{cases}1-2x^2 & ,if\ 0\le x\le 0.5\\ 0, & if\ x>0.5\ and\ x<0\end{cases} \qquad (14)$$

It is noted that if $d_k(F_j)=0$, then $H_k=0$, and if $d_k(F_j)\ge 0.5$, then $H_k=1$, in case of p=1. The value of the index H_k increases monotonically as the value of $d_k(F_j)$ increases monotonically in the interval [0, 0.5]. On the other hand, the value of the index H_k decreases monotonically as the value of $d_k(F_j)$ decreases monotonically in the same interval. Hence, if most of the patterns are clustered around the center, then the value of the index H_k would be low. In such a case, the compactness of these patterns $F_j \in C_k, j=1,2,....,p$ is high. On the other hand, if the value of the index H_k is high, then the compactness of the intraclass set is low. That means the patterns are far from the center. The compactness index H_k stands for the intraclass ambiguity for all patterns $F \in C_k$ to class C_k.

3.2 Separation index

Similar to definitions in the measure of intraclass ambiguity, some definitions are modified for the measure of the interclass ambiguity. Let $m_{kk'i}$ be the center of classes C_k and $C_{k'}$ along the ith feature axis, $k\ne k'$, $k,k'=1,2,...,l$, the normalized Euclidean distance between the pattern and the center of the two classes C_k and $C_{k'}$ is defined as

$$d_{kk'}(F_j)=\left[\sum_{i=1}^{n}\left(\frac{|F_{ij}-m_{kk'i}|}{\alpha_{kk'i}}\right)^2\right]^{1/2}, \quad F_j \in C_k \cup C_{k'} \qquad (15)$$

and

$$\alpha_{kk'i}=N_2 \cdot \max_j |F_{ij}-m_{kk'i}|, \quad F_j \in C_k \cup C_{k'} \qquad (16)$$

where factor $\alpha_{kk'i}$ is the normalization factor such that the value of $d_{kk'}(F_j)$ would lie in the interval [0, 0.5] and N_2 is a positive real number. The interclass ambiguity between two classes can be obtained by computing the index of fuzziness (Kaufmann entropy) [11] for all patterns in the given two classes. Namely, we have

$$\gamma_{kk'}=\frac{1}{p}\Big[\sum_{j=1}^{p}\mu_{(semi-\pi)\cap(\overline{semi-\pi})}(d_{kk'}(F_j^k))+\sum_{j=1}^{p}\mu_{(semi-\pi)\cap(\overline{semi-\pi})}(d_{kk'}(F_j^{k'}))\Big] \qquad (17)$$

where $F_j^k \in C_k$ and $F_j^{k'} \in C_{k'}$. From the above equation, the index of fuzziness $\gamma_{kk'}$ has the minimum ($\gamma_{kk'}=0$) as the value of $d_{kk'}(F)$ equals to zero, and $\gamma_{kk'}$ has the maximum ($\gamma_{kk'}=1$) as the value of $d_{kk'}(F)=0.5$. If most of the patterns $F \in C_k \cup C_{k'}$ are clustered around the center of the two classes, then the value of $\gamma_{kk'}$ tends to zero. On the other hand, the value of $\gamma_{kk'}$ increases as the goodness of the features in discriminating classes C_k and $C_{k'}$ increases because there are less patterns around the center. The index of fuzziness $\gamma_{kk'}$ denotes the interclass ambiguity, and is called the separation index in this paper.

3.3 Fuzzy-entropy-based feature evaluation index

Based on the compactness index and the separation index, we propose a fuzzy-entropy-based feature evaluation index (FFEI), which is defined as

$$FFEI=\sum_{k=1}^{l}\frac{H_k(F)}{\sum_{k\neq k'}\gamma_{kk'}(F)+\varepsilon}\quad,\quad 0<\varepsilon<<1 \qquad (18)$$

The term $H_k(F)/(\sum_{k\neq k'}\gamma_{kk'}(F)+\varepsilon)$ closes to minimum as $H_k(F)$ tends to zero and $\sum_{k\neq k'}\gamma_{kk'}(F)$ tends to the maximum. Contrarily, the term has the maximum ($1/\varepsilon$) as $H_k(F)=1$ and $\sum_{k\neq k'}\gamma_{kk'}(F)=0$. The value of index FFEI decreases as the pattern F increases its membership value to its own class, i.e., F increases its belongingness to its class, and in the meantime, F decreases its ambiguity of interclass. On the other hand, the value of FFEI increases as pattern F decreases its belongingness to a specific class C_k, and in the meantime, it increases ambiguities to other some classes for some $k'\neq k$. Hence, the feature evaluation becomes the task of minimizing the index FFEI; i.e., one can find the optimal subset of feature space via minimizing the index FFEI.

3.4 Relative importance and weighting factors

For the purpose of minimizing the index FFEI to find the optimal feature subset, a weighting factor $\omega_i, 0<\omega_i<1$, is introduced to a feature such that the feature space can be shrunk with a degree along the feature axis. In such a way, the weighted distances of Eqns. (10) and (15) are defined as

$$d_k(F_j,\varpi)=\left[\sum_{i=1}^{n}\left(\omega_i\cdot\frac{|F_{ij}-m_{ki}|}{\alpha_{ki}}\right)^2\right]^{1/2},F_j\in C_k \qquad (19)$$

$$d_{kk'}(F_j,\varpi)=\left[\sum_{i=1}^{n}\left(\omega_i\cdot\frac{|F_{ij}-m_{kk'i}|}{\alpha_{kk'i}}\right)^2\right]^{1/2},F_j\in C_k\cup C_{k'} \qquad (20)$$

where ϖ is the weighting set, $\varpi=(\omega_1,..\omega_i,.....,\omega_n)$, $0<\omega_i<1$, $i=1,2.....,n$. Now the index FFEI is a function of the weighting set ϖ. According to pattern recognition literatures [19][1] and our previous study [9], the weight ω_i can be viewed as reflecting the relative importance of feature F_i in measuring the similarity (in terms of distance) of a pattern to a class. The higher the value of ω_i is, the greater the importance of F_i in discriminating a class or distinguishing between classes is. After finding the set ϖ for which the FFEI is minimum, each important degree of features can be found and then one can select salient features from the n-dimensional feature set. Thus, the feature mining becomes the task of minimizing the index FFEI subject to the set ϖ.

3.5 Minimization of FFEI via GA

The task of minimization may be performed with various techniques [8][15][5]. The gradient descent algorithm is frequently used to solve the problem with an analytic solution, but a local minimum and a complex process of deviation are often followed. For avoiding falling into a local minimum, the genetic algorithm (GA) is a good choice as long as the genetic operations, such as population size and mutation rate, are properly determined. The GA searches for a population of solutions rather than a single solution. This differs from conventional optimization methods, and provides the merit of global optimum. Here we use a standard GA [5] to search the optimal weighting set. The block diagram of the GA is shown in Fig. 3, in which the fitness function is the summation of inverse of the value of index FFEI for all populations in a generation.

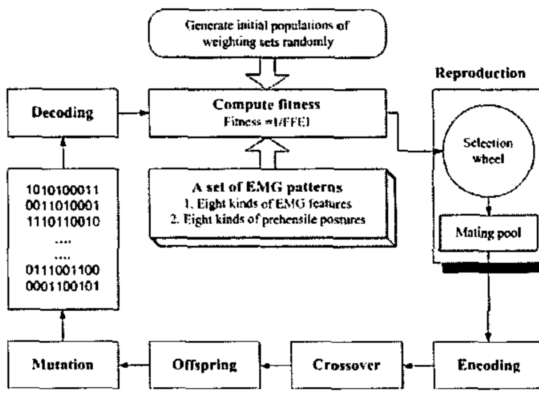

Fig. 3 Block diagram of GA in one generation

4. EMG Classification System

In this system developed in our Lab. [3][16] (see Fig. 4), EMG signals are acquired from the amputee via the EMG surface electrodes and sampled by the AD converter AD7874 with sampling frequency 2.5 KHz and then stored in the memory. Then, the sampled EMG raw data is transferred from the memory to PC by parallel port and recorded in a specified file. The feature extractions are written in the digital signal processor (DSP) in the system. The algorithm of SFM is developed with MATLAB 5.3 in a Pentium IV-1.8 GHz. PC and is performed in a PC-based offline process.

The on-line EMG signal classification module is developed and is based on the DSP TMS320C31 produced by Texas Instruments. Namely, all algorithms including feature extraction methods and classifier are embedded into the DSP. In our experiment, for reducing the effect of noise to the EMG signals, a 60 Hz. notch filter is embedded into the module. Also, for obtaining meaningful EMG signals, a 30-400 Hz. band pass filter is also embedded. The above are developed with the assembly language of TMS320C31. The output of classifier indicates which posture should be executed and the DSP will send the command to the prosthetic hand, NTU-Hand 4. NTU-Hand 4 is a five fingered prosthetic hand with 11 degree of freedom (DOF) (see Fig. 4). When receiving the posture command, the NTU-Hand 4 will generate the actual posture output.

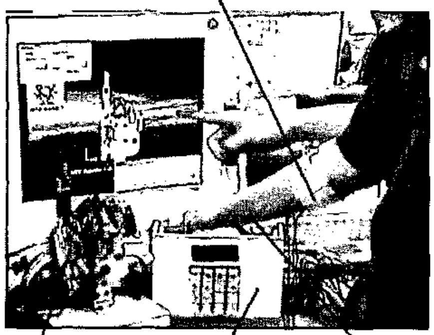

Fig. 4 EMG classification system and NTU-Hand 4

5. Experimental Results

For finding the optimal feature subset for EMG signal classification by using the proposed SFM, we prepare some EMG training data for the evaluation. Each class has 20 training patterns and each pattern contains eight kinds of features to be evaluated. The first six features are scalar, while the last two, ARM and HEMG, are feature vectors. An ARM feature is a 4-D vector and a HEMG feature is a 9-D vector. In order to transform these two kinds of feature vectors to scalars (winners), we perform two 1-D Kohonen's self-organizing maps (SOMs) [13] to find their respective feature axes. Some parameters in our SOMs are set as follows.

1) The numbers of output nodes are 100. Numbers of input nodes are 4 and 9, respectively.
2) Neighborhood size: initial value is 100 and is shrunk by [7]

$$h_{j,y_c}(t) = \exp(-\frac{d_{j,y_c}^2}{2\sigma^2(t)})$$

where d_{j,y_c} is the lateral distance between winner y_c and excited neuron j in the 1-D output space, and $\sigma(t)$ is defined as

$$\sigma(t) = 100\exp(-\frac{t}{200\log 100})$$

Therefore, as time t increases, the width $\sigma(t)$ decreases at an exponential rate, and the topological neighborhood shrinks in a corresponding manner.

3) Learning rate: initial value is 0.9 and is updated by

$$\eta(t) = 0.9\exp(-\frac{t}{200})$$

Hereafter, it will decrease gradually, but we set its minimum value at 0.01

All the 20 ARM and HEMG features are fed into the two 1-D SOMs to learn weight vectors. The learning is stopped when the mean square error (MSE) almost keeps at a small constant. Finally, all 4-D ARM features can be represented by their corresponding 1-D winners on the output nodes, and all 9-D HEMG features can be represented by 1-D winners, too.

Since all training patterns are prepared well, the next step is to perform SFM to find the relative importance of the eight features. Before using GA to minimize the index FFEI, some GA operations should be set first. All weighting factors are randomized in [0,1] initially, and then encoded to binary 10-bit strings (chromosomes). Therefore, the resolution of a weighting factor is 1024 in [0,1] such that the relative importance can be obtained more precisely. Some other operations are listed in Table 2. Besides, a roulette wheel selection is used as the evolution operation. The fitness function is defined as the inverse of the index FFEI, and the cost of each generation is defined as the summation of values of index FFEI of all populations in a generation. A genetic algorithm search with 400 generations is called a run. There are three runs in our experiment such that the results can be compared objectively. Finally, optimal weighting factors and ranks of the three runs are listed in Table 3. The generation-cost diagram of the first run is shown in Fig. 5. These weighting factors are determined when the convergence curve keeps at a constant. The rank of a feature is determined by its corresponding weighting factor, ω, i.e., the relative importance.

Table 2. GA operations setting in the experiment

String length	Crossover rate	Mutation rate	Crossover point	Population size
10-bit binary chromosome	1	0.05	Randomly search	80

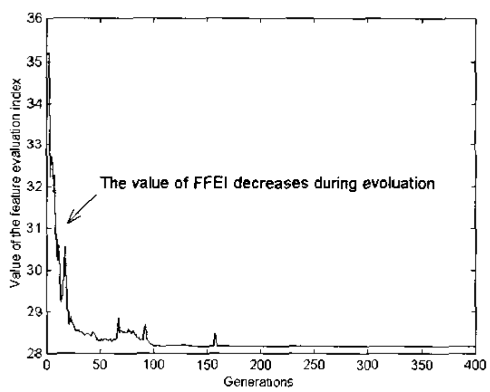

Fig. 5. Generation-cost diagram: using GA to minimize

FFEI subject to the weighting set. (The first run)

As a result, one can see that the features ARM and HEMG are the best two features in the three runs. It is worth noting that the weighting factors are not the same in each run. It may be due to the initial populations in GA generated randomly. However, the ranking levels in the three runs are nearly the same. There exists a great difference in the values of weighting factors between the two features, ARM and HEMG, and the other six features. Especially, the relative importance of features ARM and HEMG are nearly equal to each other. Also, the four features, VR, ZC, SSC, and WAMP, are quite bad because their weighting factors are quite small. The IEMG and WL occupy ambiguous positions because their respective weighting factors are in a middle region in contrast with others.

Table 3. Optimal weighting factors and ranks of features

	The first run		The second run		The third run	
	i	Rank	i	Rank	i	Rank
IEMG	0.2107	3	0.2997	3	0.2321	4
WL	0.2034	4	0.2330	4	0.3405	3
VR	0.1104	5	0.0544	5	0.1000	6
ZC	0.0550	7	0.0455	6	0.0787	7
SSC	0.1020	6	0.0243	7	0.1458	5
WAMP	0.0289	8	0.0233	8	0.0122	8
ARM	0.5766	2	0.7124	2	0.7001	1
HEMG	0.8745	1	0.7665	1	0.6790	2

Table 4. Comparison of classification rates among different features of EMG data by *K*-NN classifier (%)

	PG	HG	WF	LP	FH	CEG	TJC	CYG
IEMG	55	70	90	75	70	55	45	80
WL	45	60	100	85	70	60	65	75
VR	40	65	95	95	55	45	50	80
ZC	35	60	100	90	60	65	25	40
SSC	60	50	100	80	85	70	45	70
WAMP	40	35	100	65	50	55	45	45
ARM	90	85	95	100	75	75	70	75
HEMG	80	95	100	80	100	75	95	80

Table 5. Average classification rates of different features of EMG data by *K*-NN classifier (%)

IEMG	WL	VR	ZC	SSC	WAMP	ARM	HEMG
67.5	70	65.63	59.38	70	54.38	83.13	88.13

So far, we have found out the feature subset {ARM, HEMG} with higher ranking, and the feature subset {IEMG, WL, VR, ZC, SSC, WAMP} with lower ranking by the SFM. In order to demonstrate the validity of the ranking from the SFM, the *k*-nearest neighbor (*K*-NN) algorithm [13] is used as the classifier to obtain the classification rates for individual features. For avoiding the existence of a tie, the k is set as an odd value, k=5. The classification results for different postures are listed in Table 4. The average classification rates are listed in Table 5. From the results in Table 4, we can find that the features ARM and HEMG obtain high classification rates for all postures especially for HEMG. The classification rates of all postures are above 80%. On the other hand, the other six features get lower classification rates except for the third posture, the wrist flexion. From the classification results in Table 5, we can find that the features ARM and HEMG get higher average classification rates than others.

6. Conclusions

In this paper, we propose a method (SFM) for solving the automatic feature selection from a large amount of EMG features, which had been used before. SFM found that the two features, forth-order *autoregressive model* (ARM) and *histogram of EMG signals* (HEMG), are the better two features for the EMG classification than others (for the eight kinds of prehensile postures). In the experiments, some classification results based on *K*-NN method verify the validity of feature ranking results obtained from SFM.

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