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Human body signal detection based on multiple parameters of muscle electrical conductivity and human pulse signal

Xi Li[1], Shuangxi Gao[2,*]

Abstract. In order to improve the correct recognition rate of surface EMG signals, a surface EMG recognition model simultaneously with surface EMG feature selection and support vector machine parameter optimization is proposed. The model firstly extracts the surface EMG signal feature by wavelet transform, makes selection and support vector machine parameter optimization by genetic algorithm, and builds the optimal surface EMG signal recognition model. The simulation result shows, the genetic support vector machine improves the surface EMG signal recognition rate with better robustness. The model well solves the difficulties in the traditional method and improves the average correct recognition rate of surface EMG signal, with very stable recognition result, to offer a kind of new recognition method for the surface EMG signal.

Key words. EMG signal Human signal Parameter setting Wavelet transform Recognition
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1. Introduction

As the surface EMG signal can reflect the nerve and muscle functional status, accurately recognizing the surface EMG signal is of important meaning to the clinical medicine, sport medicine, rehabilitation medicine and sport [1].

Surface EMG signal is a kind of weak signal and easily to be interfered by the external noise source. Therefore, the collected surface EMG signal contains high noise data [2]. At present, the surface EMG signal is mainly extracted by wavelet

[1]School of Electrical and Information Engineering , Wuhan Institute of Technology, Wuhan, Hubei, 430205, China

[2]College of Mechanical and Electrical Engineering, Huanggang Normal University, Huanggang, Hubei Province, 438000, China

transform. However, when extracting the EMG signal by wavelet transform, there is a high feature dimension acquired, with large amount of repeated information among features. Hence, it has large computation complexity if making signal recognition with total features directly inputted into the classifier. Therefore, how to choose the most useful surface EMG feature signal, to reduce the surface EMG feature dimension, lower the computation complexity and improve the correct recognition rate of surface EMG signal, is the first difficulty in the surface EMG signal recognition research [4]. Based on the structure risk minimization principle, the support vector machine is specially aimed at the small-sample, high-dimensional nonlinear model recognition problem, with excellent generalization ability, so that the support vector machine becomes the main classifier for surface EMG signal [5,6]. When building the surface EMG classifier by applying the support vector machine, the parameter optimization of support vector machine shall be done, but there is no efficient parameter optimization method at present. Therefore, the parameter optimization of support vector machine is the second difficulty in the surface EMG signal recognition research [7].

2. Recognition principle of surface EMG signal

Surface EMG signal is a kind of bio-electric phenomenon, reflecting the nerve and muscle functional state, which is a kind of feature map of complex subcutaneous muscle electrical activity synthesized in the time and space. The generation principle of surface EMG signal is as shown in Fig.1.

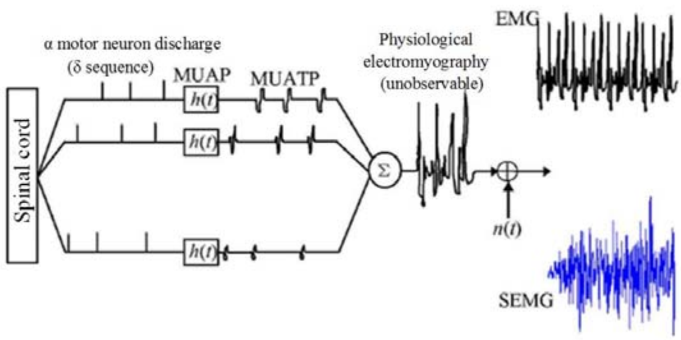

Fig. 1. Generation principle of surface EMG signal

From Fig.1, it can be known that, the amplitude range of surface EMG signal is 0∼1.5mv, with bandwidth of 0.5∼2kHz, as well as main energy centralized within 50∼150Hz, which is the sum of electricity discharge of many motor units, while the waveform is interferential and it is hard to distinguish the waveform of single unit movement. The surface EMG signal is easy to be interfered by the external noise source due to its weakness, so as to have low signal to noise ratio. Therefore, during the recognition process of surface EMG signal, it is of great significance to extract the EMG signal of good robustness and large resolution [8].

Wavelet transform has better time resolution on the high frequency part of signal, and better frequency resolution on the low frequency part, which can extract useful feature quantity from the surface EMG signal carrying with noise. The genetic algorithm is a kind of heuristic search method and has global searching ability, which can find optimal feature vector rapidly [9]. The surface EMG signal recognition process of genetic support vector machine is as shown in Fig.2.

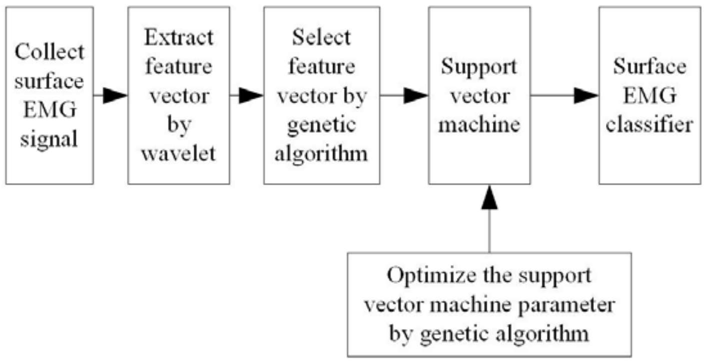

Fig. 2. Recognition process of surface EMG signal

3. Feature extraction of surface EMG signal

For the EMG signal under different function status, the wavelet transform can observe its frequency change under different scales. The wavelet transform is defined as:

$$WT_f(a,\tau) = \frac{1}{\sqrt{a}} \int f(t)\phi(\frac{t-\tau}{a})dt\,. \tag{1}$$

In the formula: $\phi(t)$ is the wavelet basis function; signifies the time displacement; a signifies the extension scale.

Because the surface EMG signal is slow in motor direction and instantaneous muscle contraction, it can use wavelet to make multi-scale filter. Different wavelet decomposition coefficients can describe the signals at different degree, so that the wavelet decomposition coefficient can depict the features of surface EMG signal. By making the wavelet decomposition on the EMG signal, the frequency coefficient matrix is gotten. The research selects the maximum valve, singular value and energy of wavelet coefficient as the features of surface EMG signal.

(1) The maximum valve of wavelet coefficient signifies the maximum value of every layer of signal frequency, so it is appropriate to regard it as the signal feature. The formula for maximum value of wavelet coefficient is:

$$\lambda_i = \max\left(|S_i|\right)\,. \tag{2}$$

Of which, Si is the decomposed sub-frequency band, $i = 1, 2, \cdots, level + 1$.

In order to lower the influence of EMG signal amplitude change caused by motor dynamics, make the logarithm process for the maximum value of every wavelet coefficient. Therefore, the feature vector constituted by the maximum value of wavelet coefficient:

$$feature = \{\log 10(\lambda_i), = 1, 2, \cdots, level + 1\} \ . \tag{3}$$

(2) By multilayer decomposition on the EMG signal, level+1 signal sub frequency bands Si is obtained, and then a singular value σi is obtained for every sub frequency signal Si by singular value decomposition. Take the singular value of every sub frequency band as the feature vector:

$$feature = \{\sigma_i, = 1, 2, \cdots, level + 1\} \ . \tag{4}$$

(3) By multilayer decomposition on EMG signal, obtain level+1 signal sub frequency bands Si, and then the average energy of Si sub frequency signals is:

$$E_i = \frac{1}{N_i} \sum_{j=1}^{N_i} \left| s_i^j \right|^2 . \tag{5}$$

In the formula, N_i is the signal length of Si.

In order to lower the influence of EMG signal amplitude change caused by motor dynamics, make the logarithm process for the average value of wavelet energies at every sub frequency band. Take the energy at every sub frequency band as the feature vector:

$$feature = \{\log 10(E_i), = 1, 2, \cdots, level + 1\} \ . \tag{6}$$

So far, the feature quantity extraction of surface EMG signal is completed. After extracting the feature, there is a high feature space dimension, enabling the surface EMG signal classifier to have a long training time, with complex design, so that it is necessary to reduce the feature space dimension.

4. First difficulty-feature selection of surface EMG signal

(1) Individual coding. The genetic algorithm individual represents the solution to feature vector of surface EMG signal and take binary coding way, of which every bit is corresponding to a given feature: “1” signifies that the corresponding feature is within the feature subset, while “0” signifies the corresponding feature is not within chosen feature subset.

(2) Fitness function design. The feature selection of surface EMG signal is to improve the correct rate of signal classification and lower the computation complexity, so that the individual fitness function is defined as the correct classification rate of surface EMG classification model constituted by the feature subset represented by individual, namely:

$$f(x) = \frac{p}{total} \times 100\% \ . \tag{7}$$

(3) Selection way design. Sort the individuals in population according to the

individual and fitness value, select the individual by roulette algorithm, and then increase the probability of better individuals entering into the next generation.

(4) Crossover way design. Randomly select two individuals to make single-point crossover operation according to the crossover probability.

(5) Mutation operation. Make individual mutation by mutation probability. Randomly select one in the individual chromosome, and mutate according to the rule of $0\rightarrow1$ and $1\rightarrow0$.

The feature selection process of surface EMG signal is as shown in Fig.3.

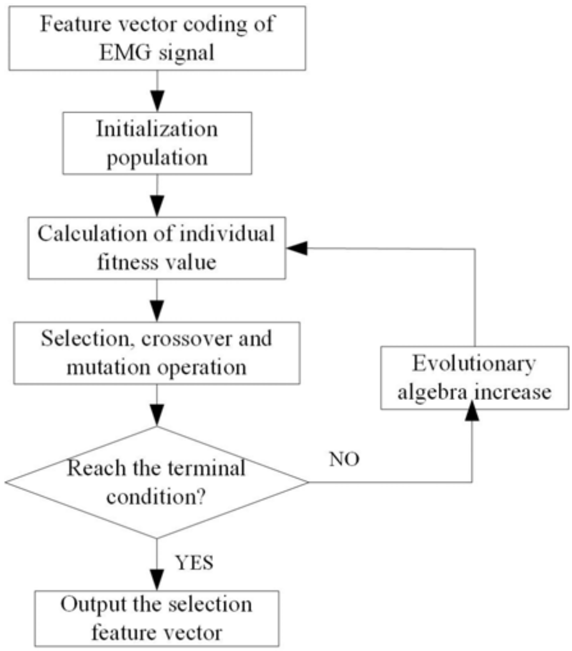

Fig. 3. Selection process for feature vector of surface EMG signal

5. Classifier construction of optimal surface EMG signal

5.1. Classification algorithm of support vector machine

For the binary-classification liner classification problem, give the dataset: (x_i, y_i), $x_i \in R^n$ and $y_i \in (1, -1), i = 1, 2, \cdots, n$, and represents the classification property. The classification of support vector machine is to find the optimal hyper-plane, which can be described as:

$$y = w^T \phi(x) + b \ . \tag{8}$$

In the formula, w and b are parameters.

For the transformation of non-linear classification problem into the quadratic optimization problem, namely:

$$\min J(w,\xi) = \frac{1}{2}\left\|w\right\|^2 + c\sum_{i=1}^{n}\xi_i \, . \tag{9}$$

In the formula, c is the penalty parameter.

Constraint condition is:

$$\begin{array}{r} y_i(w \cdot \Phi(x_i) + b) \geq 1 - \xi_i \, , \\ \xi \geq 0, i = 1, 2 \cdots , n \, . \end{array} \tag{10}$$

In the formula, $\xi = (\xi_i, ..., \xi_l)^T$.

For the classification of large sample, solve by introduce the Lagrange multiplier and transforming into dual problem, then the decision function of support vector machine:

$$f(x) = sign(\sum_{i=1}^{n} \alpha_i y_i (\phi(x) \cdot \phi(x_i)) + b) \, . \tag{11}$$

In the formula, $sign$ is the sign function, and α_i is the multiplier.

Replace the dot product $(\phi(x) \cdot \phi(x_i))$ by kernel function $k(x_i, x)$. Finally, the classification decision function of support vector machine is changed to:

$$f(x) = sign(\sum_{i=1}^{n} \alpha_i y_i k(x_i, x) + b) \, . \tag{12}$$

The result of recognition of support vector machine to surface EMG signal is directly related to the parameter. Therefore, the support vector machine parameter is selected by genetic algorithm.

5.2. Classifier design of surface EMG signal

Support vector machine only can make two-classification, cannot be directly used in the multi-class problem classification [10]. For a multi-class model recognition problem like the surface EMG signal, the support vector may solve by “one-to-many” strategy and “one-to-one” [10]. The “one-to-many” algorithm usually create the refused classification, therefore, the research applies the “one-to-one” strategy, and combines with the dichotomy discrimination tree to build the multi-layer classifier. Fig.4 is the structure chart of the 7th classifier among 8 kinds of classifiers.

5.3. Recognition steps of surface EMG signal

(1) Choose the support vector machine function. Because of the well-adapted radial basis function, the research selects it as the kernel function of support vector machine and sets the valuation range of C and radial basis function width σ.

(2)Extract the surface EMG signal feature by wavelet.

(3)Select the feature vectors extracted by wavelet by genetic algorithm.

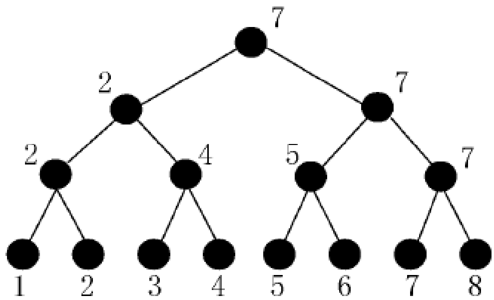

Fig. 4. Structure chart of "one-to-one" binary tree classifier

(4)Learn by inputting the selection feature quantity into the support vector machine, and optimize its parameter by genetic optimization, to build the optimal surface EMG signal classifier.

(5)Test by inputting the training sample into the established classifier, and inspect the classifier performance.

6. Simulation experiment

6.1. Data source

In order to test the performance of recognition algorithm of surface EMG signal proposed by the research, apply specific data to make simulation experiment. The recognition movements are 8 kinds of internal rotation wrist, external wrist rotation, fist making, fist extension, upper cut, lower cut, internal palming and external palming, as well as four kinds of wrist flexion, wrist extension, inward rotation of wrist and outward rotation of wrist. A surface EMG signal sampled from 1 subject is as shown in Fig.5, and a total of 200 surface EMG signals are collected, of which the first 160 groups of signals are taken as training sample and the last 40 groups of signals are taken as the test sample.

6.2. Model realization

Make feature extraction on eight kinds of action surface EMG signals among all sample signals by wavelet transform, take 4 for the wavelet sub-band value, get 12 feature vectors in this way, select 12 feature vectors by genetic algorithm, obtain 7 optimal feature vectors finally, input 7 feature vectors selected by training sample into the support vector machine to learn, optimize the support vector machine parameters by genetic algorithm, obtain the optimal parameters c=50 and σ=0.917 by 10-fold crossover verification, build optimal surface EMG signal recognition model by optimal feature subset and optimal parameters, test the test sample, and inspect the performance of established surface EMG signal recognition model.

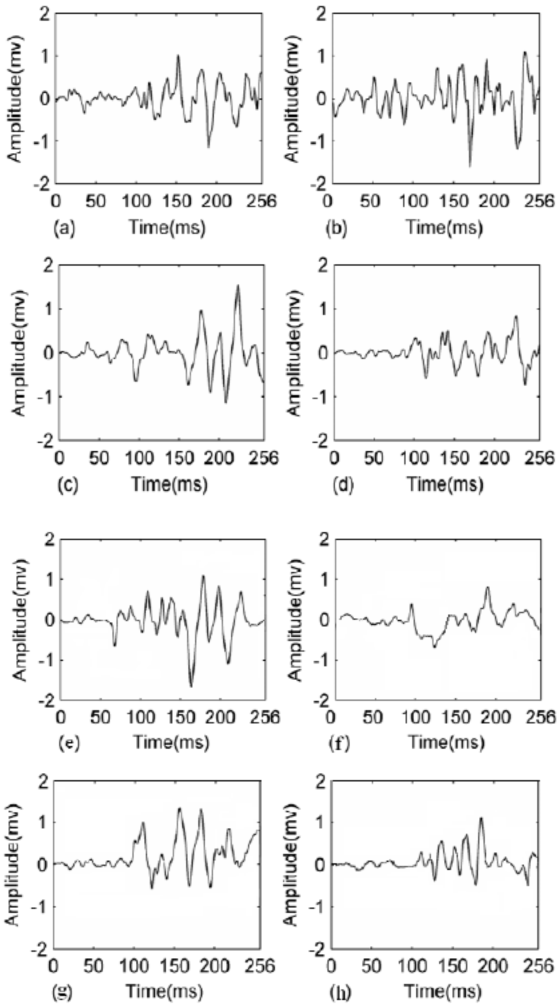

Fig. 5. Surface electromyography of eight types of movements

6.3. Result and analysis

In order to make the recognition result of EMG recognition method proposed by the research be more convincing, the comparison model is: wavelet transform + support vector machine (WA-SVM), without feature selection and parameter optimization being carried out; wavelet transform + genetic optimal support vector machine (WA-GASVM), which only optimizes the support vector machine by genetic algorithm, without feature selection being carried out; wavelet transform + BP neural network (WA-BPNN), which makes feature selection by genetic algorithm, and optimizes BP neural network parameter by genetic algorithm. The tradition network search is applied. They are tested for 5 times, with average recognition rate as the evaluation standard of model performance. Their average recognition rate is as shown in Table 1.

Table 1. Average recognition comparison of several kinds of models (%)

Model	WA-SVM	WA-GASVM	WA-BPNN	Model in this paper
Internal rotation wrist	97.35	98.42	96.09	98.57
External wrist rotation	90.77	92.21	89.39	94.98
Fist making	93.27	96.4	92.88	96.99
Fist extension	89.25	94.24	95.1	96.39
Upper cut	97	99.21	98.48	99.25
Lower cut	97.38	97.85	96.67	98.55
Internal palming	92.15	95.16	82.57	99.24
External palming	94.81	97.82	94.38	97.92
Average recognition rate	94.00	96.41	93.20	97.74

From the result of Table 1, it can be known that, in all models, the recognition model of surface EMG signal proposed by the research has best performance, so that the following conclusion can be gotten:

(1) Aiming at the non-stationary property of surface EMG signal, make the scale decomposition on signal by wavelet transform with multi-differentiation feature, extract the singular valve, maximum value and energy of wavelet decomposition coefficient as the feature of surface EMG signal, of which these features is stable and easy to be recognized etc.

(2) Aiming at the information redundancy among the wavelet extraction features, select the feature vector of surface EMG signal by genetic algorithm, efficiently reduce the feature space complexity, quicken the recognition speed of surface EMG signal and improve the recognition rate.

(3) Design the surface EMG signal classifier by BP neural network and support vector machine classifier, of which their average recognition rates are up to 93% all and have very stable recognition result, with strong robustness.

(4) Support vector machine has a obviously higher recognition rate than BP neural network, mainly caused by the easy trap into over-learning and poor generalization ability of neural network method based on experiment and risk minimum on a large scale. Moreover, the support vector machine gives consideration to training error and generalization ability at the same time, with certain superiority in solution of nonlinear, small-sample and high-dimensional model recognition problem.

7. Conclusions

Upon research on recognition problem of surface EMG signal, as the surface EMG signal contains large amount of noise with high feature dimension, the traditional method cannot eliminate the noise and just select the most important recognition feature signal, with low correct recognition rate of surface EMG signal. In order to improve the correct recognition rate of surface EMG signal, a kind of new surface

EMG signal recognition model is proposed. Firstly, extract the surface EMG signal feature by wavelet transform, eliminate the noise in signal, select the optimal feature signal by genetic algorithm, reduce the feature dimension, and optimize the support vector machine parameters by genetic algorithm, to build the recognition model of optimal surface EMG signals. The simulation experiment shows, compared with the traditional recognition algorithm, the genetic support vector machine efficiently improves the average recognition rate of surface EMG signal, with stable recognition result and good robustness. Moreover, the method is also applicable to the analysis and treatment of other non-linear stable signals.

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