EMG Classification for Prehensile Postures Using Cascaded Architecture of Neural Networks with Self-Organizing Maps

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Abstract

Electromyograph (EMG) features have the properties of large variations and nonstationarity. An important issue in the classification of EMG is the classifier design. The major goal of this paper is to develop a classifier for the classification of eight kinds of prehensile postures to achieve high classification rate and reduce the online learning time. The cascaded architecture of neural networks with feature map (CANFM) is proposed to achieve the goal. The CANFM is composed of two kinds of neural networks: an unsupervised Kohonen's self-organizing map (SOM), and a supervised multi-layer feedforward neural network. Experimental results show that by extracting EMG features, forth-order autoregressive model (ARM) and histogram of EMG signals (IEMG), as inputs, the proposed CANFM can obtain and remain higher classification rates compared with other classifiers, including k -nearest neighbor method (K -NN), fuzzy K -NN algorithm, and back-propagation neural network (BPNN) in several online testing.

Keywords: EMG classification, prosthetic hand, self-organizing map (SOM), and neural networks.

1. Introduction

EMG classification for controlling a prosthetic hand is one of the most difficult pattern recognition problems because there often exist large variations in EMG features. Hence, how to select a suitable classifier that can handle large variations existed in EMG features to remain high classification rates and can have fast response to output posture command in the online process is very important.

The k -nearest neighbor (K -NN) algorithm and neural networks were frequently selected as the classifiers in the EMG classification in the practical use [1][7][14][16]. The K -NN algorithm is based on the distance (e.g. Euclidean distance) similarity matching [9]. It has the merits of simplicity. However, it cannot handle features with complexity since there are no machine learning techniques involved. Besides, the back-propagation neural network (BPNN) appears more robust to solve complex classification problems since BPNN can learn the relationship between inputs and desired outputs of training patterns by gradient descent technique and back-propagation algorithm [6][11]. However, if number of inputs increases, the complexity of network structure will increase exponentially. In [1], they took the

back-propagation algorithm to train fuzzy rules to build a fuzzy inference based neural network classifier to handle the variation property. In [4], they combined the linear discriminant algorithm (LDA) with the principal component analysis (PCA) to classify EMG signals based on wavelet features. However, for some other features (e.g. time-domain features), using the LDA may not be a good solution due to the high interclass ambiguities. Moreover, the required time for classification is another consideration.

To handle complicated EMG classification problems accurately and efficiently, we develop a new cascaded architecture of neural networks with feature map (CANFM) to classify EMG signals. In the proposed classifier architecture, CANFM, the dimension of feature space is first reduced by the unsupervised neural network, Kohonen's self-organizing map (SOM). No matter how many features are used, each group of features in high dimension from a channel (an EMG surface electrode) can be transformed into two-dimensional (2-D) coordinates by the 2-D Kohonen's SOM. Aside from the benefit of reduction in input dimension, SOM can remove some noisy data and can absorb the large variations appear in original features. Thus, it can avoid the subsequent training process being over-oriented to the training patterns. The further classification will be performed by a supervised multi-layer neural network trained by back-propagation algorithm (BPNN). The classification process by the CANFM is performed on the digital signal processor (DSP) based EMG classification system.

2. EMG Data Acquisition

2.1 Prehensile Postures and Sensor Locations

In this paper, eight types of prehensile postures to be classified are selected for the reason that they are typical postures for most frequent use of 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.

In order to obtain the 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 [8], 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)

Table 1 Eight kinds of 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

2.2 EMG Feature Extractions

Some EMG features, such as integral of EMG (IEMG) [7][16], waveform length (WL) [7][16], variance (VAR) [14][15][16], zero crossing (ZC) [7][15][16], slope sign changes (SSC) [7][16], Willison amplitude (WAMP) [14][16], autoregressive model (ARM) [14][5][16] and histogram of EMG (HEMG) [14], have been proposed. In this paper, we select the ARM and HEMG as the EMG features through some testing and evaluation.

Fig. 1. The placements of EMG surface electrodes

A. 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

$$y_k = -\sum_{i=1}^M a_i \text{emg}_{k-i} + w_k \quad (1)$$

where y_k is the k th 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 method (LMS). The adaptive AR method that is similar to the adaptive predictor predicts the input EMG sample according to previous input samples by minimizing the output error. The adaptive predictor structure is shown in

Fig. 2.

Fig. 2 Adaptive linear predictor

The criterion of the adaptive LMS method is to minimize a mean square error function $E[e^2(n)]$ that can be given as

$$e(n) = y(n) - \hat{y}(n) = y(n) - \sum_{i=1}^N a_i y(n-i) = A^T Y(n) \quad (2)$$

where A represents the linear prediction vector, $Y(n)$ is the input signal vector by

$$A = \begin{bmatrix} 1 \\ a_1 \\ \vdots \\ a_N \end{bmatrix}, \quad Y(n) = \begin{bmatrix} y(n) \\ y(n-1) \\ \vdots \\ y(n-N) \end{bmatrix} \quad (3)$$

thus

$$E[e^2(n)] = A^T E[Y(n)Y^T(n)] A \quad (4)$$

In order to minimize $E[e^2(n)]$ with respect to prediction vector A , the gradient of $E[e^2(n)]$ is used to obtain the optimum as

$$\frac{\partial E[e^2(n)]}{\partial A} = 2E[Y(n)Y^T(n)] A = 2E[Y(n)e(n)] \quad (5)$$

The prediction vector A can be updated by the following steepest-descent algorithm:

$$A(n+1) = A(n) - \beta \frac{\partial E[e^2(n)]}{\partial A} = A(n) - 2\beta E[Y(n)e(n)] \quad (6)$$

It can be further simplified as

$$A(n+1) = A(n) - 2\beta e(n)Y(n) \quad (7)$$

where β is a constant rate of convergence. For each adaptive coefficient, we have

$$a_i(n+1) = a_i(n) - 2\beta e(n) \text{emg}(n-i) \quad \text{for } i=1 \dots M \quad (8)$$

where $a_i(n)$ is the original ARM parameter, β is a constant rate of convergence and $e(n)$ is the difference between the n th sample data of EMG raw data and the n th output of ARM. Hence, we can update the new ARM parameter by Eq.(8). A model order of 4 is adequate for AR time series modeling of EMG signal. The simulation of the original EMG signal using a fourth-order AR model is shown in Fig. 3. Correspondingly, an ARM feature contains four feature components.

B. 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 [14], 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 feature contains nine feature components

Fig. 3. The simulation of the original EMG signal using a fourth-order AR model

3. Cascaded Architecture of Neural Network with Feature Map (CANFM).

CANFM is a cascaded architecture of neural networks. It is composed of two neural networks. The former is the unsupervised Kohonen's self-organizing map (SOM), the latter is the supervised multi-layer feedforward neural network trained by back-propagation algorithm (BPNN). Fig. 4 shows detailed information of the proposed CANFM. There are three input channels in the CANFM. The three channels receive features extracted from EMG signals of palmaris longus, extensor digitorum and flexor carpi ulnaris, respectively. Each channel sends features as the input of the Kohonen's SOM and the output is the 2-D coordinate (on the x and y axes) in the 2-D topological net. A 2-D coordinate is thus a condensed feature for a channel. After the feature map, these condensed features become new input of the BPNN. In this way, there are total six input nodes of the BPNN due to three channels.

Fig. 4 Detailed information of CANFM

The cascaded architecture can compensate for the inaccuracy of unsupervised neural network and long training time of supervised neural network. Another

important contribution of the proposed cascaded architecture is to reduce the input dimension (feature space) of the post-classifier. Although the concept of cascading a supervised neural network with an unsupervised neural network is not a new concept to reduce the training time of a supervised neural network, the proposed architecture is a brand new idea for dealing with the reduction of dimension of feature space in EMG classification research field. In addition, SOM can map a space with variations onto a small cluster in the 2-D map by the concept of neighborhood [11][10]. This offers us a great benefit for the EMG classification. Actually, in our previous study [13], we had implemented a similar cascaded architecture of neural networks for handwritten digits recognition. According to the experimental results of handwriting recognition, such classifier can achieve high recognition rate to handwritten features which have large variations due to different styles of people.

3.1 Reduction of Input Dimension by 2-D SOM

The 2-D Kohonen's SOM can keep the neighborhood relations of the input pattern since it learns under the topology-preserving map [10]. Therefore, the 2-D SOM is also called a topology-preserving map. The merit is useful for clustering EMG signals. In addition, the Kohonen's SOM can be used to remove the redundancy in feature space or noise information in the input pattern, and avoid the trial and error approaches, such as genetic algorithm and KL expansion. In other words, the 2-D Kohonen's SOM reduces the input dimension from a high dimension to a 2-D coordinate.

The unsupervised SOM can find a winner on the 2-D map to represent the original pattern which is in high dimension. Let y_c be the corresponding output neuron (winner node) of a high dimensional vector x on the 2-D output net, the location of y_c can be found by the following four steps according to the learning rule of the Kohonen's feature map [6].

Step 1: Initialization. Choose random values for the initial weight vectors $W_j(0)$. The only restriction here is that the initial weight vectors $W_j(0)$ must be different for $j=1, \dots, l$, where l is the numbers of output neurons.

Step 2: Similarity Matching. Find the winning neuron y_c at time step t by using the

minimum-distance Euclidean criterion:

$$y_c = \arg \min_j \|x(t) - W_j(t)\|, j = 1, 2, \dots, I \quad (9)$$

Step 3: Updating. Adjust the synaptic weight vectors of all neurons by using update rule

$$W_j(t+1) = W_j(t) + \eta(t)h_{j,y_c}(t)[x(t) - W_j(t)] \quad (10)$$

where $\eta(t)$ is the learning rate, and $h_{j,y_c}(t)$ is the neighborhood function centered around the winner; both $\eta(t)$ and $h_{j,y_c}(t)$ are varied dynamically during learning for best results.

Step 4: Continuation. Go back to step 2 until no changes in the feature map are observed.

The learning rate in step 3 should be time varying. This requirement can be satisfied by choosing an exponential decay for $\eta(t)$

$$\eta(t) = \eta_0 \exp\left(-\frac{t}{\tau_1}\right), t = 0, 1, 2, \dots, \quad (11)$$

where τ_1 is the time constant of the learning rate. The learning rate begins with a value in (0,1); thereafter it would decrease gradually. But we keep it above 0.01. Correspondingly, the topological neighborhood function is assumed a time-varying form as

$$h_{j,y_c}(t) = \exp\left(-\frac{d_{j,y_c}^2}{2\sigma^2(t)}\right) \quad (12)$$

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

$$\sigma(t) = \sigma_0 \exp\left(-\frac{t}{\tau_2}\right) \quad (13)$$

where τ_2 is another time constant of the SOM algorithm, and σ_0 is the value of σ at the initiation. Therefore, as time t increases, the width $\sigma(t)$ decreases at an exponential rate, and the topological neighborhood shrinks in a corresponding manner

3.2 Classification by Back-Propagation Neural Network

After reduction of the input space using Kohonen's SOM, the three sets of 2-D coordinates (six newly condensed features) are fed into the BPNN for further classification. Choosing the BPNN as the post-classifier of CANFM is due to its learning ability and fast recall speed. Since there are eight postures to be classified, the BPNN has eight output nodes (see Fig. 4) and one hidden layer in which the number of hidden nodes should be determined based on experimental trail-and-error to achieve near-optimal learning accuracy. Which posture should be executed will depend on which output neuron has the largest value in the recall process of the neural network. In the learning of connected weight vectors, the generalized

delta learning rule [11] for the weight updating is used in this paper. Also, a sigmoid function is used in a neuron for the nonlinear transformation of aggregated signals from input nodes.

4. EMG Classification System

The system architecture is shown in Fig. 5. At first, the EMG signals are acquired from the EMG surface electrodes and sampled by the AD converter AD7874 with sampling frequency 2.5 KHz and then stored in the memory. An EMG raw data has 1000 samples, i.e., an EMG raw data is obtained in 400 ms. Then, the sampled EMG raw data is transferred from the memory to PC by parallel port and recorded in a specified file.

Fig. 5 Block diagram of the EMG classification system

Feature extraction methods (ARM and HEMG) and classifications (CANFM) are embedded in DSP with its own assembly codes [3].

The on-line EMG signal classification module is developed based on the DSP chip TMS320C31 produced by Texas Instrument. In our experiment, for reducing the effect of noise to the EMG signals, a 60 Hz notch filter is embedded into the module. In addition, for obtaining meaningful EMG signals, a 30-400 Hz band pass filter is embedded. The above are developed with the assembly language of TMS320C31. The output of CANFM indicates which posture should be executed and the DSP-based EMG classification system will send the command to NTU-Hand IV. NTU-Hand IV is a five fingered prosthetic hand with 11 degree-of-freedom (DOF) (see Fig. 6). When receiving the posture command, the NTU-Hand IV will generate the actual posture output.

5. Experimental Results

An illustrative example for the classification of the features from three channels using CANFM is shown in Fig. 7, and it gives the details of the system. First, we obtain EMG signals from three channels, and then extract the ARM and HEMG features. For each channel, an ARM feature contains four feature components, while a HEMG feature contains nine feature components. After acquiring the input features, we pass each group of the features (13 feature components per channel) into a Kohonen's SOM. Then, each group of features with high dimension is reduced to 2-D coordinates. We use the three sets of 2-D coordinates as inputs of the supervised BPNN classifier. The result we obtained is the desired class, and its name is Hoop Grasp. Finally, the prosthetic hand, HTU-Hand IV,

follows the classification result to perform the same posture.

Fig. 6 Real picture of DSP-Based EMG classification and NTU-Hand IV performing on an amputee

Fig. 7. An illustrative example for classification of the features using CANFM

In our experiments, parameters in the unsupervised 2-D SOM are set up as follows. The three 2-D SOMs for all channels have the same numbers of input nodes (one SOM has 13 input nodes, where 4 input nodes belong to ARM, 9 input nodes belong to HEMG). The output topological net for a SOM is arranged as a 20-by-20 2-D net. The initial neighborhood size is 20. For the learning rule, the initial learning factor η_0 is set as 0.9, and time constant τ_1 is 200. The initial neighborhood size is equal to the number of output neurons, such that all output neurons will have the chance to be the winner of the corresponding input at beginning. Therefore, the initial size σ_0 is equal to the radius of the 2-D output net (10). The time constant for the

neighborhood function is $\tau_2 = 200/\log \sigma_0$. Besides, for the neural network BPNN in the CANFM, the number of input node of this BPNN is 6, and number of output node is 8. The number of hidden node is set as 10. The BPNN used here is trained by the standard back-propagation learning [11] rule with momentum term, where the learning rate is set as 0.3, the momentum parameter is set as 0.9. The network structure, as well as the learning constants, is determined after thorough trail-and-error testing for achieving the best performance (i.e., lowest MSE). The learning stops when the MSE almost keeps constant (2000 learning cycles used here).

Table 2. Comparison of the classification results among K-NN, fuzzy K-NN, BPNN, and CANFM (%)

	PG	HG	WF	LP	FH	CEG	TJC	CYG	Ave.
K-NN	90	100	100	85	80	95	85	95	91.25
Fuzzy K-NN	90	100	100	85	90	95	85	95	92.50
BPNN	100	100	100	85	100	100	95	100	97.50
CANFM	100	100	100	95	100	95	100	100	98.75

Table 2 shows the classification results of the K-NN method (For avoiding the existence of a tie [9], the k is set as 5 here, an odd value), fuzzy K-NN algorithm [9], pure BPNN, and CANFM. Each posture has 20 training patterns and 20 testing patterns. The features used for all classifiers are ARM and HEMG features. Again, by taking trial-end-error to achieve near-optimal structure, the numbers of input node, hidden nodes, and hidden nodes in this pure BPNN are 39, 20, and 8, respectively. The learning rate and momentum constant of the BPNN are the same as the setting of BPNN in CANFM (0.3 and 0.9).

Fig. 8. MSE of pure PBNN against BPNN in CANFM

Table 2 shows that the CANFM outperforms the K-NN, fuzzy K-NN, and BPNN in average classification accuracy by 7.5%, 6.25% and 1.25%, respectively. Fig 8 shows the MSE of the pure BPNN against BPNN in our CANFM. We can conclude that the pure BPNN is insufficient to reduce learning time and the MSE due to the complexity of the EMG signals and large network structure, but our CANFM can tackle this problem successfully. The learning of pure BPNN appeared slow compared with the learning of BPNN in CANFM (MSE approaches zero). Therefore, by cascading Kohonen's SOMs to reduce the feature space

can actually speed up the learning time of a BPNN and reduce MSE. However, the EMG system does not reset. Namely, the EMG surface electrodes are remaining on the same locations when extracting training patterns and testing patterns.

In order to test the robustness of CANFM against the variations of features, except the test data used in Table 2 (the 1st test), we prepare another two test sets (each test set has 160 testing patterns, and each posture has 20 testing patterns too) in different days. It implies that the muscles' conditions may be different, relax or tight. In particular, when re-acquiring a new testing set, the EMG surface electrodes are replaced.

Table 3. Classification results (%) (2nd test)

	PG	HG	WF	LP	FH	CEG	TJC	CYG	Ave.
K-NN	15	55	0	50	45	0	40	40	30.63
Fuzzy K-NN	25	70	0	60	60	0	45	60	40.00
BPNN	85	80	45	85	90	40	45	75	68.13
CANFM	95	100	100	100	95	100	100	100	98.75

Table 4. Classification results (%) (3rd test)

	PG	HG	WF	LP	FH	CEG	TJC	CYG	Ave.
K-NN	45	50	95	60	60	0	0	100	57.50
Fuzzy K-NN	95	60	95	70	70	0	0	100	61.25
BPNN	90	60	70	90	75	20	50	80	62.50
CANFM	100	90	100	100	100	100	100	80	96.25

Table 3 and Table 4 show the classification results of the 2nd and the 3rd tests, respectively. We see that for some postures, K-NN method and fuzzy K-NN show no discrimination abilities. For example, the postures WF and CEG cannot be recognized by K-NN and fuzzy K-NN (classification rates = 0). Besides, the BPNN shows better classification results than K-NN and fuzzy K-NN in most of postures in the 2nd and the 3rd test. However, the BPNN gets lower classification rates compared with the results in the 1st test. Moreover, CANFM still gains high classifications rates for all postures no matter how poor the results of the other three classifiers are. Finally, the average classification rates from these three test results are shown in Fig. 9. Clearly, CANFM remains higher average classification rates in the 2nd and the 3rd test (above 96.25%), while classification rates obtained from K-NN, fuzzy K-NN and BPNN drop a lot from the 2nd test.

Fig. 9. Comparison of average classification rates of different tests among different classifiers

6. Conclusions

In this paper, a cascaded architecture of neural networks with feature map (CANFM) is proposed to enhance and remain the EMG classification accuracy under large variations of EMG signals. Several conclusion remarks are as follows:

1. By using feature set {ARM, IEMG}, we experience three tests to obtain the classification results for eight kinds of prehensile postures by using K-NN, fuzzy K-NN, BP neural network, and CANFM.
2. Another important contribution of CANFM is that the learning time is reduced substantially because of the reduction of input dimension by cascading SOM for each channel (each EMG surface electrode).

In short, this paper proposes CANFM to approach optimal EMG classification. Moreover, we develop a DSP-based EMG classification system to realize the on-line EMG classification combined with the multi-DOF prosthetic hand, NTU-Hand IV., which had been developed in our Lab.

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