NEW PARAMETERS FOR EMG CLASSIFICATION

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ABSTRACT

In this work, a classification method for electromygraphic (EMG) signals is presented. Dynamic programming is used during the selection of the feature vectors. Artificial neural network and distance classifiers are used for classification processes. The obtained classification results are reported to be promising.

I. INTRODUCTION

The EMG signals observed at the surface of the skin is the sum of thousands of small potentials generated in the muscle fibers. The signal can be used as a control source of artificial limbs after it has been processed. Different features have been used by several authors to classify the EMG signals; time domain features [1], autoregressive (AR) coefficients [2], cepstral coefficients [3], wavelet coefficients [4]. In this paper, new features are used for identification of arm movements such as elbow extension, elbow flexion, forearm supination and forearm pronation. After the features are extracted from the EMG signals, the reduced numbers of effective ones are selected by dynamic programming.

II. DYNAMIC PROGRAMMING

The EMG signals consist of segments of four different movements. A segment of a movement belongs to biceps or triceps muscles. So, the features are extracted from the EMG segments obtained from biceps and triceps muscles. Each segment goes through windowing process by Hamming window. Each segment is about 256 ms long, thus each segment can be assumed as stationary segments. AR (autoregressive) coefficients (1), prediction error (PE) (2), squared prediction error (FPE) (3), final prediction error (fpe) (4), energy features (E) (5), median frequency (f_{med}) (6), mod frequency (f_{mod}) (7) and average frequency (f_{avr}) (8) are extracted from the segments as features [5]:

$$x(k) = -\sum_{i=1}^{p} a_i . x(k-i) \tag{1}$$

$$\text{PE}=\sum_{i=1}^{N} \left| x_i - \hat{x}_i \right| \tag{2}$$

$$FPE = \sum_{i=1}^{N} (x_i - \hat{x}_i)^2 \tag{3}$$

$$fpe = \sum_{i=1}^{N} \frac{PE(i)^2}{(N+1-p)} \frac{(1+p/N)}{(1/p/N)} \tag{4}$$

$$\text{E}=\sum_{i=1}^{N} \frac{\max(x_i{}^2)}{\frac{1}{N}(x_i{}^2)} \tag{5}$$

$$\int_0^{fmed} S_m(f).df = \int_{fmed}^{\infty} S_m(f).df = \frac{1}{2}\int_0^{\infty} S_m(f).df \tag{6}$$

$$f_{avr}=\frac{\int_0^{\infty} f.S_m(f).df}{\int_0^{\infty} S_m(f).df} \tag{7}$$

$$\text{fpe}=\sum_{i=1}^{N} \frac{PE(i)^2}{(N+1-p)} \frac{(1+p/N)}{(1/p/N)} \tag{8}$$

where x_i is the original signal, $\hat{x}_i$ is the AR prediction of x_i, N is the number of time samples of x_i, f is the frequency, $S_m(f)$ is the power spectral density of the signal and p is 4 for the AR model order. f_{mod} is the frequency of the peak value of the power spectrum. f_{med} is the frequency that divides the area staying under the power spectrum into two equal parts and E stands for the ratio of the maximum energy of the data sample to the average energy of the whole time sample.

The features, which are most suitable for the discrimination of the four classes, are selected by the help of dynamic programming method [5]. Dynamic programming method aims to select a subset of best features from a given number of features using Mahalanobis distance criterion as divergence [5]:

$$D_i^2 = (\underline{\beta} - m_i)^T W^{-1} (\underline{\beta} - m_i) \quad (9)$$

where β is the feature vector of the unknown signal, m_i is the mean value and W is the covariance matrix of the i'th class. All possible combination of feature subsets are not considered, some are ignored, in order to reduce the number of computations. The best features are the ones, which have the highest distance criterion or divergence value. The dimension of the features vector is determined as 8 for convenience and high performance. Features are computed as TPE_b, TPE_t, fpe_b, fpe_t, FPE_b, 1^{st}, 2^{nd} AR coefficients for biceps and 2^{nd} AR coefficient for triceps, which b and t denotes biceps and triceps segments respectively.

III. CLASSIFICATION

Fuzzy Mahalanobis Distance C-Means (FMDCM) method, Adaptive Fuzzy Probabilistic C-Means (AFPCM) method, Fuzzy k-Nearest Neighbourhood (k-NN) method, Bayes' Criterion (BC) method and a Neural Network (NN) ensemble are utilized to classify the EMG signals [5,6,7]. FMDCM and AFPCM methods are used to determine membership of feature vectors for k-NN type classification. The signal processing algorithms including segmentation, dynamic programming and other methods except neural network ensemble are verified as software using MATLAB 5.1 (Mathematics Laboratories) simulation program.

The EMG signals are applied to a neural network ensemble consisting of an input layer with 8 inputs, an output layer with 4 outputs and two hidden layers each having 12 neurons for classification. The eight input corresponds to the eight dimensions feature input vector that was mentioned above and four dimensions output is for the number of the classes. The neural network ensemble is trained with backpropagation algorithm in C programming and sigmoid tangent is the function used in the neurons of the hidden layers.

IV. RESULTS AND CONCLUSION

Classification rates are seen in Table 1. Discrimination ratios of the classification methods are given in Table 2, Table 3, Table 4 and Table 5.

Table 1. Classification rates

	FMDCM &k-NN	AFDCM &k-NN	BC	NN
Classification Rate (%)	80	81	78.5	75

Table 2. Discrimination ratio of FMDCM & k-NN

	EF	EE	FP	FS
EF	56	0	8	36
EE	0	94	6	0
FP	0	20	78	2
FS	0	2	6	92

Table 3. Discrimination ratio of AFDCM&k-NN

	EF	EE	FP	FS
EF	56	0	4	40
EE	0	94	6	0
FP	0	16	82	2
FS	0	0	8	92

Table 4. Discrimination ratio of BC

	EF	EE	FP	FS
EF	58	0	8	34
EE	0	90	10	0
FP	0	24	72	4
FS	0	0	6	94

Table 5. Discrimination ratio of Neural network

	EF	EE	FP	FS
EF	58	4	4	34
EE	0	90	6	4
FP	2	26	72	0
FS	0	8	12	80

The selected features by dynamic programming seem to good classify. Among four classes, the classification rate for EF is very low. In order to increase this rate, new electrode locations for EF classification could be tested. The classification rates obtained in this work are still small for clinicians in order to use them for prosthesis control purposes.

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