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NEURAL NETWORK METHODS IN APPLICATION FOR MYOELECTRICAL SIGNALS CLASSIFICATION

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Abstract – This research investigates the problem of the movement classification by surface myoelectrical signals (MES), used for electromyographical (EMG) control of powered upper limbs, and also for biometric identification of the person. On of the solutions in this task is using pattern recognition approach [1]. In this case the success of the myoelectric control scheme depends largely on the classification accuracy. The main target of the research was comparison of various neural network classifiers, such as multi layer perceptron with back-propagation learning algorithm (BPG), neural networks with radial-basis functions (RBF), probabilistic neural networks (PNN) and Kohonen`s self-organised maps (SOM) [2]. Fundamental to the success of chosen method was the sheme, which involves a wavelet based feature set, dimensionally reduced by principal components analysis (PCA), and classified by SOM classifier. It was also detected that the best accurate performance is possible when using 30 components as input vector for classifier, and four channels of myoelectric data greatly improve the classification accuracy, as compared to one channel.

Keywords pattern recognition, classification, neural networks

1. INTRODUCTION

Surface MES is a signal measured at the skin surface, which contains the information about the muscular activity. Therefore, frequency components and amplitude of these signals can be employed for definition of motion dynamics. This aspect has been adapted in many fields, such as prosthetic hand control, functional electric stimulation, and other assistant equipments for invalid persons. At present time, electromyogram (EMG) is the one of mostly employed characteristic used as the control signal source of artificial limbs.

In [3]-[7], the following conclusions concerning MES were made: a) surface MES is the superposition of multiple nonlinear transfer channels of multiple sources (muscles); b) MES has the non-stationary structure [8], because it changes with time due to fatigue of muscles and other conditions change; c) MES for different classes of movements has no well defined destinations, therefore can be overlapped; d) MES has individual variation due to difference of composition of muscles, skin thickness and fat content [4].

According to these characteristics of MES the main problem during myoelectrical control of the prosthetic devices is contained in complexity of the motion recognition, i.e. motion classification by MES. In compliance with classified information each classification system should include three main steps: **Feature extraction**, in this step feature vectors containing sufficient information for motion discrimination is generated from MES, here mainly used classical techniques to estimate the spectrum of the multi-component signal. There are short time Fourier transform (STFT), wavelet transform (WT) or wavelet packet transform (WPT). The characteristics of these methods in application for the motion classification were already compared [5], and as the result WPT method was suggested as the best for improving classification accuracy, but it should take into account that in [5] and [3] WPT was used together with PCA and linear discriminant analysis (LDA), without careful comparing between other classifiers besides MLP), therefore it was decided to repeat comparing of this methods in assembly with all types of classifiers used in this work. For details the STFT, WT and WPT, refer to [3]. **Dimensionality reduction**, in this step feature set projects from high-dimensional space to a more meaningful, lower-dimensional space. The most widely used subspace projection technique is PCA. **Classification**, in this step feature patterns are classified into same classes. This step is the kernel of the problem, the main target here is motion discrimination, various neural network classifiers can be used in this step, such as multi layer perceptron with back-propagation learning algorithm, neural networks with radial-basis functions, probabilistic neural networks and Kohonen`s self-organised maps. Each of this classifier has merits and demerits according to specific target, so in this investigation the comparison of these classifiers regard to MES classification was carried out. In [4] the fourth stage is proposed – **Evaluation** step, in this step it is supposed that the conditional information entropy of the classes formed in the third step will calculating to detect the degree of overlapping for all classes of motions. This step used when there is no knowledge about ideal number of classes, in this work we know the number of classes (8 classes, refer to Chapt.3 Experiments).

2. METHODOLOGY

MES classification system proposed here has two work modes, as follows:

Learning mode – in input of the system there is a frame of source MES $S_{n,i}(t)$ measured from channel n. This mode consists of three steps: in the first step, called Processing Unit, feature extraction from MES carried out, the result is the feature set $F_{n,i}$. The spectrums characteristics obtained by STFT, WP, WPT were used in this stage. Each feature set was extracted from a frame of MES with length L (L=300). The optimal parameters for STFT are the Hamming window for 64 points with overlapping of 50%. WT was calculated with Coiflet family of order five. For the WPT Symmlet the mother wavelet of order six was taken.

In the second step there is calculating PCA orthogonal matrix for dimension reduction of the feature set $F_{n,i}$. This procedure needs accumulating of preprocessed MES frames. In PCA, the basis vectors are obtained by solving the algebraic eigenvalue problem (1):

$$R^T(F_nF_n)^T R = A, \qquad (1)$$

where F_n is a data matrix whose columns are training preprocessed MES frames $F_{n,i}$ (this vectors must be centered), R is a matrix of eigenvectors and A is the corresponding diagonal matrix of eigenvalues. The projection of data from the original m-dimensional space to a subspace spanned by l-principal eigenvectors is optimal in the mean squared error sense (2):

$$C_{n,l} = R_l^T F_n, \qquad (2)$$

Note that, the number of the MES for PCA must be greater than the number of the components in orthogonal matrix used for dimension reduction (output size of the feature set is 30 components). In the third step the calculated patterns $C_{n,l}$ are put as training vectors in input of each neural network classifier (their principles are described thereinafter), as the result of learning neural network recieves the synaptic matrix W trained for recognition preprocessed frames of MES.

Recognition mode – in the input is a frame of source MES $S_{n,i}(t)$. The first step produces feature sets in the same procedures as in learning mode ($F_{n,i}$ in output). In the second step correction occures using the orthogonal matrix calculated in PCA, in the third step the trained classifier (neural network uses the synaptic matrix W trained in Learning mode) recognizes the movements by the current received vector of attributes $C_{n,l}$.

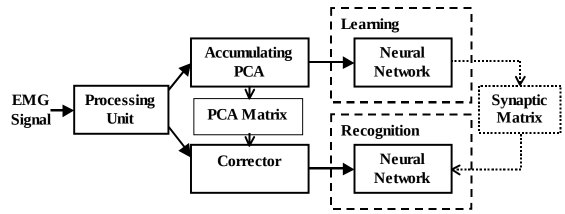

Fig.1 Layout of the MES classification system

One of the main task of the experiments was the investigation of the influence of the MES measurement channels quantity on the classification quality, how many classes can be revealed with each variant of the system, what parameters of processing block stage of the classification system [3] make the most influence on the classification quality and to find their best values.

2.1 Back-Propagation Neural Network

The resilient back-propagation (Rprop) training algorithm was used for faster back-propagation learning. The purpose of this direct adaptive method is to eliminate the harmful effects of the magnitudes of the partial derivatives. The sign of the derivative is used to determine the direction of the weight update. The size of the weight change is determined by a separate update value η: factor α for increasing, factor β for decreasing (α=1.15, β=0.30) (3-5).

$$\frac{\partial E}{\partial x_i^3} = x_i^3 - d_i, \qquad (3)$$

$$\frac{\partial E}{\partial x_i^2} = \sum_{n=1}^{N3} \frac{\partial E}{\partial x_n^3} \cdot f(u_n^3) \cdot w_{ni}^3, \qquad (4)$$

$$\Delta w_{ij}^m = -\eta \cdot sign(\frac{\partial E}{\partial x_i^m}) \cdot f'(u_i^m) \cdot x_j^{m-1}, \qquad (5)$$

where d is teacher vector consists of 0 or 1 as its components, η is an update value which determines velocity of learning, N3 – number of neurons in output layer. The calculation principle for η is as follows: if an element of gradient changes sign from one iteration to the next, then the corresponding element is decreased by β. If an element of gradient maintains the same sign from one iteration to the next, then the corresponding element is increased by α.

2.2 Neural networks with Radial-Basis Functions (RBF)

RBF neural networks provide a powerful technique for generating multivariate nonlinear mapping. Because of their simple topological structure the learning algorithm corresponds to the solution of a linear problem, and so the training of the network is rapid.

The performance of an RBF network critically depends upon the choices of the number and the centers of hidden units. Most natural choice of centers is to let each data point in the training set correspond to a center. In this case the number of degree of freedoms in the network is equal to the number of training data, and the network function fits exactly through each data point. If data have regular behavior, but are contaminated by noise, then the overfitting phenomenon will occur, which leads to the poor generalization property of the network.

In this work two-layer RBF network was used. The first layer has radial neurons (6), and calculates its weighted inputs with Euclidean distance weight function.

$$p_j = e^{-a_j \cdot d_j}, \quad (6)$$

where a_j – factor which controls probability of appurtenance of the input vector to j-th space within distance d_j.

The second layer has linear neurons, and calculates its weighted input with dot product weight function and its net inputs by summation its weighted inputs and biases.

2.3 Probabilistic Neural Networks (PNN)

PNN is a direct neural-network implementation of the Parzen nonparametric probability density function estimation and Bayes classification rule. To reduce the number of neurons minimum classification error criterion is to be used.

The original PNN structure consists of three feedforward layers: input layer, pattern layer, and summation layer. The input layer accepts the feature vectors and supplies them to all the neurons in the pattern layer. The pattern layer of pools is to intervene between the input feature vectors and the output weight vectors of the pattern neurons, N3 – number of the neurons in third layer. And the summation layer forms the weighted sum of the outputs from the pool in the pattern layer.

The training rule is the same as for BPG and RBF neural networks.

2.4 Kohonen`s self-organised maps (SOM)

The SOM is a neural network method for classification (also clustering) developed by T. Kohonen [2]. (7)

$$w_n(t+1) = w_n(t) + h_{cn}(t) \cdot (x_m(t) - w_n(t)), \quad (7)$$

where t=0,1..T are discrete time steps, $w_n(t)$ is weight for neuron n on the step t, $h_{cn}(t)$ is a heighborhood function weight adjustment.

This method is suitable in point of view visualization of the output data, because the classified vectors can be visually mapped to 3, 2 or 1 dimensional data.

For all types of neural networks used in this work the default values of weights w_o were calculated with rule (8):

$$w_o = \frac{1}{\sqrt{n}}, \quad (8)$$

where n is the weight vector length for neurons of the initial layer. Relatively to (8) each component x_i of the normalised input vector x is to be transformated with (9):

$$x_i = \alpha(t) \cdot x_i + (1 - \alpha(t)) \cdot \frac{1}{\sqrt{n}}, \quad (9)$$

where α(t) – coefficient, which changes from 0 to 1 during learning process, thus at first almost similar vectors are presented in the input layer, then thay fall to inital in.

This rule for weight initialization was choosen because the random initial weights can result in a fusion vectors of classes, which vectors densely distibuted, and contrariwise.

3. EXPERIMENTS

Two types of the experiments described here are the basis for the research. In the first experiment the system performances for different neural network classifiers were compared. The person generated three various classes of movements.

The second experiment expands previous outcomes and shows possibilities of the same system with four MES channels for eight classes of movements. All movements were carried out starting from the ordinary forearm position.

In the first experiment the data were acquired from one healthy person, the entry was carried out from the one MES channel, using of the one pair of bipolar electrodes (LR-04AM.1), located on the central part of the forearm, with the reference electrode on the wrist.

The person generated three various classes of movements: hand close, hand open and wrist flexion, as shown in fig. 2. In this experiment only three classes of movements are used according to experience of the previous researches [3,4,5,6], the one-channel system with small quantity of learning vectors physically can not be trained on more classes. The decision about using such movements was made after the practical research for the movements provided characteristic changes in MES.

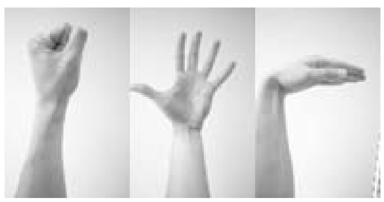

Fig. 2 Three classes of movements used in the one-channel experiment

Each bipolar channel formed by Ag-AgCl electrodes with 1 cm^2 square. The record length approximately 7000 msec (7000 points, with frequency of 2000 Hz, in frequency band - from 10 up to 500 Hz). In each set, for each class was generated 20 patterns, total quantity for class – 60 patterns. This set were subdivided on learning (15 patterns) and test (5 patterns) sets (no using the validation set is related to the small samples quantity. Such quantity of the input patterns theoretically is insufficient for teaching neural network by BPG method, but situation with little amount of learning vectors is a most realistic for application of researched system.

The main attention appeared to SOM, RBF and PNN, which are known by the ability to be trained on the limited learning sets, and for some application the single train pattern is enough for teaching PNN.

In the second experiment, MES were acquired simultaneously from four channels, using of four pairs of bipolar electrodes (such as LR-04 AM. 1), placed on the central part of the forearm, with the reference electrode on the wrist, as shown in fig. 3.

In this experiment participate three persons, each of them made the same movement types continuously for each class with an interval - 1 sec, generating 50 sec records. The first 40 sec parts of the records was used as a teaching set, and the last 10 sec was used as a test set. These sets were subdivided into 1024 points records and transferred to the learning system by the same methods as in the first experiment.

Fig. 3 Location of the first and second channels.

Each person generated eight classes of movements: hand close, wrist flexion, hand open, wrist extension, ulnar deviation, radial deviation, flexion only of a large finger, flexion of all fingers, except for large, as shown in fig. 4. All movements were carried out from the initial position (ordinary position). For each class generally 200 patterns were generated, total - 1600 records.

Fig. 4 Eight classes of movements used in four-channel experiment.

Parameters for neural networks classifiers are listed in Table 1.

TABLE I. Parameters for neural networks classifiers

Classifier	Parameters
BPG	Number of neurons in layers 1,2,3: N1 = 30, N2=40, N3=8. T=1000 epochs
RBF	N1=30, N2=1600, N3=8
PNN	N1=30, N2=1600, N3=8
SOM	Map size: 10x10, T=1000 epochs

All computation was carried out in Matlab Version 6 Release 12 using Neural Network Toolbox.

Experiments results are shown in fig.5 and fig.6.

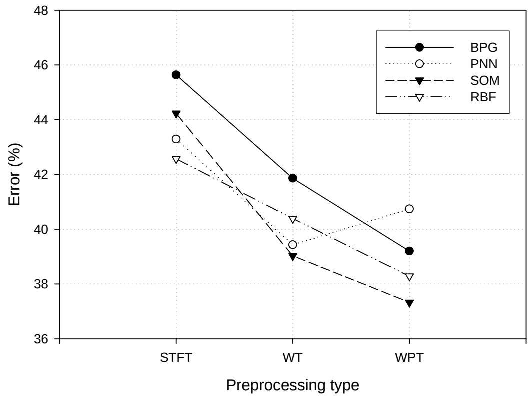

Fig. 5 Classification errors for three classes of MES using PCA, one channel

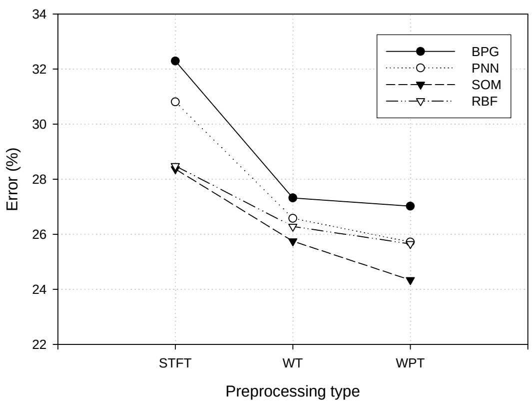

Fig. 6 Classification errors for eight classes of MES using PCA, four channels

Summing up all said above allocate main outcomes of the described investigations: a) the neural networks allow successfully decide the problem of the movements classification by MES; b) the system with MLP (BPG learning algorithm) shows the worst performance; c) the applications with Kohonen`s learning algorithm and neural network with radial-basis functions reduce the error of the classification better then other; d) for wavelet transform based feature set SOM and RBF produce practically identical error; e) the application with probability neural networks has no stability and don't repeat the tendency of the other; f) the system with WPT preprocessing and PNN classifier differs from other`s tendencies, it can be connected to small deviation of the Gaussian function, that reduces the generalization ability.

4. CONCLUSION

With the certain tuning of the neural networks we can achieve outcomes, when the recognition error for the eight classes with 1600 sample patterns of the movements is 24.6 %. For further researches directed on increasing of the efficiency of the neural networks application, it can be used the estimation criterion of the system flexibility for the recognition of the new patterns, and also deciding of the problem of stability-plasticity realized by various applications of the adaptive resonance theory principles.

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