

Neural Networks with AR Model Coefficients Applied to the EMG Signal Classification

Marek Kurzynski and Andrzej Wolczowski

Wroclaw University of Technology, Dept. of Systems and Computer Networks
Wyb. Wyspianskiego 27, 50-370 Wroclaw, Poland

Abstract. The paper presents a concept of hand movements recognition on the basis of EMG signal analysis. Signal features are represented by coefficient of autoregressive (AR) model, and as classifier the MLP and Adaline networks are applied. The performance of the proposed method was experimentally compared against four different classifiers using real datasets. The systems developed achieved the highest overall classification accuracies demonstrating the potential of neural network classifiers based on AR coefficients for recognition of EMG signals.

1 Introduction

The activity of human organism is reflected in characteristic biosignals, which can be measured and next can be applied to the control of the work of technical devices. Electrical potentials accompanying skeleton muscles (called EMG signals) are an example of such biosignals. They can be detected and registered through the skin and used to the control of bio-prosthesis.

Although in the last decade many attempts have been made to determine the hand movements on the base of EMG signal analysis ([5, 10, 11, 13]), the reliable recognition of kind of grasp is still a hard problem. The difficulty increases along with the prosthesis dexterity (prosthesis movement repertoire), therefore it is still a need for research in developing EMG signal recognition.

The paper presents a concept of recognition of hand movements (type of grasp) on the base of EMG signal analysis. Signal features are represented by autoregressive (AR) model coefficients, and as classifier the MLP and Adaline network are applied.

The performances of proposed classification systems were compared against four (statistical (Bayes, kernel), fuzzy and k-nearest neighbours) classifiers using real datasets. For the purpose of experimental investigations a special measurement stand was elaborated which allow us synchronous recording the image of the moving hand and multi-channel registration of EMG signals.

The paper is divided into three sections and organized as follows. In section 2 we provide an insight into the analysis of EMG signals which is the basis for the recognition of grasps. In Section 3 computer experiments on real data are described and their results are discussed.

2 EMG Signal Analysis

The recognition of hand movement on the basis of the myopotentials comprises three stages [13]: (1) the acquisition of the EMG signal; (2) extraction of the features differentiating the movements; (3) classification of the signal.

Each stage has an influence on the quality of the whole process, i.e. reliability of the grasping movement recognition.

2.1 EMG Signal Acquisition – the Measurement Stand

The block diagram of the designed measurement stand for EMG signal acquisition and identification of the relation between the hand movement and simultaneously created myopotentials, is presented in Fig. 1. The stand includes: (1) a video camera for recording the image of the moving hand; (2) specially designed 8-channel EMG signals measuring circuit (Bagnoli Desktop EMG System, DelSys); (3) the PC computer recording the results of the acquisition, equipped with high fidelity measurement board, containing 8 independent A/D converters (24 bits per channel) and USB port for USB video camera; (4) an application for synchronous recording of the video and EMG data streams and their analysis.

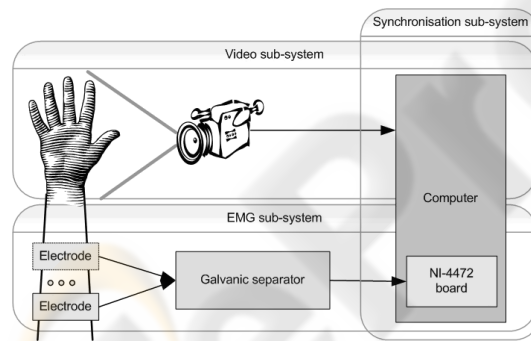


Fig. 1. The measurement system for identifying the relation between the hand movement and EMG signals.

2.2 Features Extraction

The extraction of features consists in determining such parameters that best differentiate the received signals for the sake of movement recognition. The extraction of features can be accomplished using various techniques including signal amplitude, EMG frequency characteristic and power spectrum analyzed by fast Fourier transform (FFT) method [6], the integral of the absolute value (IAV) and zero crossing signal [6, 7], time and frequency histograms [11], among others. In this paper it is proposed an efficient method to determine the input features based on autoregressive (AR) model.

The AR model belong to a group of linear prediction methods that attempt to predict an value y_n of a time series of data $\{y_n\}$ based on the previous values $(y_{n-1}, y_{n-2}, \dots)$.

Deriving the linear prediction model involves determining the coefficients (a_1, a_2, \dots, a_p) in the equation:

$$\hat{y}_n = \sum_{k=1}^p a_k y_{n-k}, \quad (1)$$

where \hat{y}_n is the estimated value of signal in a time n , a_k are the AR coefficients and p is the order of AR model.

Several estimators of AR coefficients are well known in the field of signal processing. We chose the Burg algorithm because of its many remarkable advantages (it does not apply window data, minimizes forward and backward prediction errors, gives high resolution for short data records, always produces a stable model) [9]. The Burg algorithm estimates the AR coefficients by fitting an autoregressive linear prediction filter model of a given order to the signal. Consequently, the Burg algorithm determines for each channel the set of p AR coefficients, which create the feature vector describing the EMG signal (r is the number of channels):

$$x = [a_{11}, a_{12}, \dots, a_{1p}, a_{21}, a_{22}, \dots, a_{2p}, \dots, a_{r1}, a_{r1}, \dots, a_{rp}]. \quad (2)$$

2.3 Classification

Two types of artificial feedforward neural networks were used in this study for classification of EMG signal: multilayer perceptron (MLP) and Adaline network.

1. **The MLP Classifier (MLP).** The network consists of the input, hidden, and output neuron layers. The input layer plays the role of a data buffer so that the data are normalized to belong to the $[0, 1]$ range. There have been various numbers of input and hidden layer neurons, depending on the actual quantities of data. The number of output layer neurons is equal to the number of classes (types of grasps). The final classification is made according to the maximum rule. Both the hidden and output layer neurons have the sigmoid transition function. Neurons of the successive layers are connected on the each-to-each basis. In the experiments, the corresponding layers were trained by means of the error back propagation method with momentum term.
2. **The Adaline Classifier (ADA).** The single layer neural network that contains neurons with (positive) linear transfer functions. As previously, the number of neurons is equal to the number of classes and the final classification is made according to the maximum rule. In the experiments the Adaline network was trained by Widrow and Hoff learning procedure, also known as the delta rule.

3 Experiments

The proposed methods of EMG signal classification based on ANN techniques were experimentally tested and their performances were compared against the four following pattern recognition techniques: (1) Naive Bayes method (NB) [4]; (2) Parzen classifier with the Gaussian kernel and the optimal smoothing parameter (PAR) [4]; (3) 5-nearest neighbours classifier (5-NN) [4] and (4) classifier based on fuzzy relations (FR) [13].

3.1 Experimental Setup

The experiments were carried out on healthy persons. The electrodes, connected to the respective measuring channels, were put over the following forearm muscles: (1) the extensor muscle of the fingers, (2) the radial extensor of the wrist, short, (3) the superficial flexor muscle of the fingers, (4) the ulnar flexor muscle of the wrist, (5) the extensor muscle of the thumb, short, and (6) the flexor muscle of the thumb, long (see Fig. 2).

The experiments were conducted in MATLAB using PRTools and NN Toolbox.

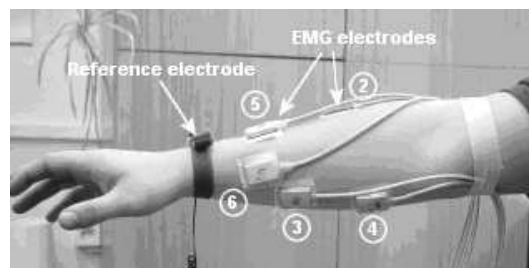


Fig. 2. The layout of the electrodes on the forearm.

In experiments five different types of grasps (classes) presented in Fig. 3 were chosen for recognition from the set defined by Schlesinger ([8]): 1) palmar, 2) tip, 3-4) cylindrical and cylindrical tight, 5) spherical. Our choice is deliberate one and results from the fact that the control functions of simple bioprosthesis are hand closing/opening and wrist pronation/supination, however for the dexterous hand these functions differ depending on grasped object [2].



Fig. 3. Types of grasps recognized in experiment.

Each measurement lasted 2.5 s and was preceded with a 10 s break. In that way for the single grasp movements the discrete signals were obtained each of a size of 2500 samples (1 kHz sampling frequency) \times 6 channels, together with the video sequences related to them, that picture the movement types (classes). The 300 measurements (60 measurements for each grasp type (class)) were created, and next gathered EMG signals were subjected to the feature extraction procedure for different orders of AR model p equal to 2, 3, 5, 7 and 10. Consequently, we got 5 datasets, each containing 300 patterns described by 12, 18, 30, 42 and 60 features, respectively. The training and testing datasets were extracted from each dataset using two-fold cross-validation method.

The ADA classifier comprised 5 neurons which inputs number was equal to the number of features (different for each dataset). Similarly, the MLP classifier comprises 5 neurons in the output layer and the number of input neurons (hidden neurons) was equal to 12 (8), 18 (10), 30 (15), 42 (20) and 60 (30) for the successive datasets, respectively. The number of epochs in the learning procedure for the both ANN classifiers was equal to 200.

3.2 Results and Discussion

Classification accuracies (i.e. the percentage of correctly classified objects) for methods tested are listed in Table 1. The accuracies are average values obtained over 10 runs (5 replications of two-fold cross validation). Statistical differences between the performances of the ADA, MLP classification methods and the four classifiers were evaluated using Dietterich’s 5x2cv test [3]. The level of $p < 0.05$ was considered statistically significant. In Table 1, statistically significant differences are given under the classification accuracies as indices of the method evaluated, e.g. for the dataset with $p = 5$ the MLP classifier produced statistically different classification accuracies from the NB, 5-NN and FR methods. The row “Mean” contains results averaged over all datasets.

Table 1. Classification accuracies of classifiers compared in the experiment (description in the text). The best score for each dataset is highlighted.

AR order	Classifier / Mean (SD) accuracy [%]					
	NB ₁	PAR ₂	5-NN ₃	FR ₄	ADA	MLP
$p = 2$	73.2(5.2)	82.8(2.8)	86.5(4.2)	72.4(6.3)	84.2(3.1) 1,4	87.7 (2.2) 1,2,4
$p = 3$	79.3(4.6)	90.2(1.9)	94.2 (1.6)	80.6(2.4)	91.0(1.3) 1,4	93.6(1.2) 1,2,4
$p = 5$	81.5(2.2)	97.6 (0.3)	85.3(1.4)	83.5(3.6)	94.8(1.1) 1,4	97.4(0.6) 1,3,4
$p = 7$	80.4(2.5)	98.2(0.7)	95.8(0.9)	87.2(1.3)	98.3(0.2) 1,3,4	100 (0.0) 1,3,4
$p = 10$	82.7(2.3)	98.1(0.5)	96.9(0.4)	91.5(1.2)	100 (0.0) 1,2,3,4	100 (0.0) 1,2,3,4
Mean	79.4(3.4)	93.4(1.2)	93.8(1.7)	83.0(2.9)	93.7(1.1) 1,4	95.7 (0.8) 1,2,3,4

The MLP classifier achieved the highest overall classification accuracy averaged over all datasets – it outperformed the NB, PAR, 3-NN and FR classifiers by 16.3%, 2.3 %, 1.9% and 12.7% on average, respectively. The ADA neural network that was the third best-scoring classifier, outperformed the NB, PAR and FR systems by 14.3%, 0.3% and 10.7% on average, respectively. The both ANN-based classifiers produced statistically significant higher scores in 29 out of 40 cases (5 datasets × 4 classifiers × 2 systems developed). The ADA and MLP classifiers also achieved the highest classification accuracy (i.e. 100%) when the datasets with 42 and 60 features were used.

Furthermore, they produced the best stability (the SD values of 1.1% and 0.8% averaged over all datasets), followed by the PAR classifier (1.2%). Results obtained indicate, that proposed methods of grasping movement recognition based on the AR model as an EMG signal feature extraction procedure, produced accurate and reliable decisions, especially in the cases with greater number of features.

References

1. Boostani R., Moradi M., Evaluation of the forearm EMG signal features for the control of a prosthetic hand, *Physiological Measurement* 24 (2003), 309-319
2. De Luca C., J., Adam R., et al., Decomposition of surface EMG signals, *Journal of Neuropsychology* 96, (2006) 1646-1657
3. Dietterich T.G., Approximate statistical tests for comparing supervised classification learning algorithms, *Neural Computing* 10 (1998) 1895-1923
4. Duda R., Hart P., Stork D., *Pattern Classification*, John Wiley (2000)
5. Ferguson S., Dunlop G., Grasp recognition from myoelectric signals, *Proc. 2002 Australasian Conference on Robotics and Automation* (2002) 83-87
6. Kuribayashi K., Okimura K. and Taniquichi T., A discrimination system using neural network for EMG-controlled prostheses, *Proc. Int. Conf. IEEE Robot and Human Communication* (1992) 63-68
7. Khoshaba T., Badie K., and Hashemi R., EMG pattern classification based on back propagation neural network for prosthesis control, *Proc. Ann. Int. Conf. IEEE Eng. Med. Biol. Soc.* (1990) 1474-1475
8. Reaz M., Hussain M., Techniques of EMG signal analysis: detection, processing, classification and applications, *Biological Procedures Online* 8 (2006) 11-35
9. Schloegl A., A comparison of multivariate autoregressive estimators, *Signal Processing* 9 (2006) 2426-2429
10. Wang, G., Zhiguo, Y., Xiao, H., et al., Classification of surface EMG signals using harmonic wavelet packet transform, *Physiol. Measurement* 27 (2006) 1255-1267
11. Wojtczak P., Amaral T., Dias O., Hand movement recognition based on biosignal analysis, *Engineering Applications of Artificial Intelligence* 22 (2009) 608-615
12. Wolczowski A., Kryztoforski K., Control-measurement circuit of myoelectric prosthesis hand, *Acta Bioengineering and Biomechanics* 4 (Suppl.) (2002) 576-578
13. Wolczowski A., Kurzynski M., Human-machine interface in bioprosthesis control using EMG signal classification, *Expert Systems* 27, (2010) 53-70