HAND PROSTHESIS CONTROL
Software Tool for EMG Signal Analysis

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Abstract: The paper discusses the problem of the decision process of controlling the bio-prosthesis of the hand that is treated as the human intention recognition by means of the analysis of the electromyography (EMG) signals from the hand muscles. The number of movements, which is indispensable for the dexterity of the prosthesis, makes the recognition not entirely reliable. The approach presented herein includes three methods: the decision tree, neuron networks, and genetic algorithms in order to enhance the reliability of the EMG signal recognition. Simultaneously, the paper presents the software designed for the needs of the research and adapted to processing the EMG signals in compliance with these methods.

1 INTRODUCTION

The dexterity of the human hand is the result of both its kinematic structure and the control of it by the central nervous system. The construction of multi-joint anthropomorphic mechanic structure that can copy even very complicated movements of the human hand poses at present no problem. However, the question of the reliable bio-control of such a dexterous prosthesis remains unsolved.

The usual practice is to make use of myopotentials – which are electrical signals that accompany the activity of the muscles (Wolczowski, 2001). This is feasible since, after the amputation of the hand, there remain in the stamp a significant number of the muscles that earlier controlled the movement of the fingers (Su Y, et al., 2007; Mohammadreza, 2007). Through the tensing of these muscles, the person with a disability may express their intentions to control their prosthesis as they do with their healthy hand. The intention recognition calls for efficient analysis of EMG signals. Taking into account a large number of possible movements that characterize a dexterous hand, the chances of error occurrence are high. The minimization of this error occurrence constitutes the current challenge in devising the person-prosthesis interface. The experiments on the recognition of the movement intended by a person with an amputated hand can be replaced with the analysis of the relationship that holds between the movements of the healthy hand and the myopotentials that occur then, taking into consideration the limitations that arise due to the lack of some of the muscles in the amputated hand.

The solution presented here consists in the decomposition of the recognition, which leads to the multi-stage process that can be presented as the decision tree (DT).

In order to reduce the occurrence of recognition errors irrespective of the number of the processed data we have opted for replacing the usual decision nodes with Neural Networks of the multilayer perceptron (MLP) type (enodes). In order to create an MLP population, we have made use of the Genetic Algorithm (GA), which enhanced the synthesis of optimal MLPs.

For the needs of the research "EMG Analysis" application has been developed, which allows for the program transformation of the registered signals. Its operation is described in detail in subsequent chapters. Initially the EMG signal in the form of numerical data is transmitted to the SQL database. Signal acquisition and the manner in which the accumulated data are being refined are described in Chapter two. Chapter three describes methods of EMG signal analysis; extraction of characteristic features and concept for signal classification. Chapter four describes the experiment that has been carried out and sums up the results.

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2 EMG SIGNALS ACQUISITION

In order to classify the EMG signal (or to determine the class of the intended movement) one has to make a number of transformations of the obtained signal, which boils down to its multistage analysis. Each of the said stages affects the quality of the whole process that is the reliability of movement recognition. That is why it is so important for each of the stages to be optimised as to their reliability and calculability. Main stages of the process that are being carried out by "EMG Analysis" application are presented below.

2.1 Signal Acquisition

In order to obtain the data the EMG signal was measured by means of 8-channel measuring system (Krysztoforski and Wolczowski, 2005). The system is made up of: (a) – computer that register the results of the measurements; it is fitted with (b) - A/D converters card (Ni 4477); and (c) - 8 active differential electrodes. The electrodes are fitted with two metal contacts (De Luca, 2006) that are directly integrated with the circuit amplifying the measured signals (potentials difference).

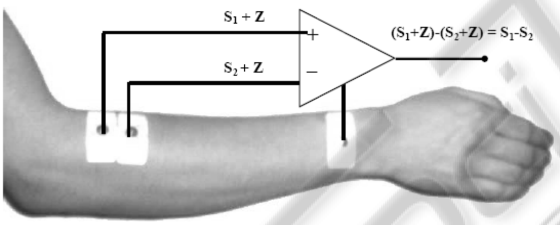

Figure 1: The differential measurement method. The EMG signal is represented by 's' and the noise signals by 'z'.

That kind of construction makes it possible to eliminate most of the disturbances that occur during the measurement. The value of the reduction is determined by coefficient CMRR of the amplifier. In this system the coefficient amounts to 84dB.

The signals from the electrodes are transformed into a digital form that is convenient for further analysis on the A/D converters card and they are stored in the SQL database of the measuring computer. These data are labelled for their further identification (measurement number, class of problem – i.e. posture). Data acquisition carried out in this way enables further program transformations of the obtained EMG signal by means of consecutive application modules of "EMG Analysis".

2.2 Preparing the Data for the Analysis

In order to reduce the level of noise in the obtained EMG signal, the signal undergoes an initial processing that consists in averaging of the signal course in the domain of time, independently of each channel (1), according to the rule:

$$y[n] = \alpha * x[n] + (1-\alpha) y[n-1] \qquad (1)$$

y[n] - current output sample from averaging system;
x[n] - current EMG sample.

The selection window placed in the form shown in Figure 2 marked as "alpha coefficient" enables the operator to select a proper degree of the signal averaging depending on its quality ($\alpha \in \langle 0.5, 1.0 \rangle$).

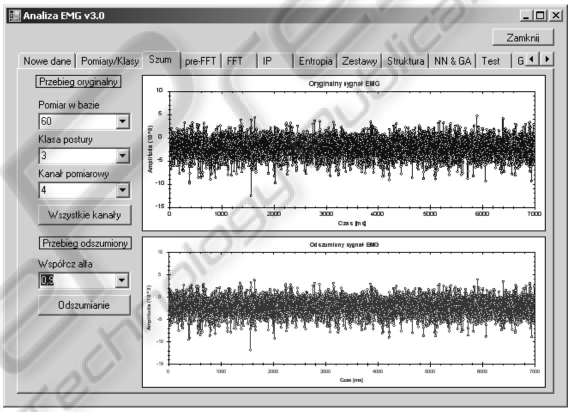

Figure 2: Actual signal (upper part of the figure), the filtered signal. The alpha parameter equals 0,9.

The signal that has been processed as described above may be used for identifying characteristic features i.e. such features that differentiate the analysed signals one from another (in consequence the type of the hand movement).

3 EMG SIGNAL ANALYSIS

The process of EMG signal recognition is made up of two main stages: that of determining the features of the measured signal and that of signal classification on the basis of the determined features (Wolczowski and Suchodolski, 2007).

3.1 Features Extraction

In order to determine characteristic features of the signal two methods have been applied: Fast Fourier Transform and Wavelet Transform.

To carry the task out, the signal amplitude had to be analysed (Wojtczak, et al., 2008). A low-amplitude signal is difficult to classify due to the participation of the constant constituent (in the form of noise) and also due to the fact that the low value of the signal amplitude may imply both that the muscle (the hand) is at rest or its insignificant participation in a given class of movement. The analysis has been carried out according to the following scheme:

- Division of the input data vector that consists of 7.000 samples/channel (7s measurement) into 40 element windows (40 ms), and calculation of the sum of the contents each window (E_{sum}). In this way the information of the energy of the recorded movement is obtained; the minimum E_{min} and the maximum E_{max} energy values in the set;
- Finding out the energy threshold E_{edg} (activateing energy) in accordance with rule (2). In this way a group of windows is singled out that may contain important information in relation to the signal for the calculations that are being carried out (level of the signal amplitude);
- The Windows that fulfil the energy condition $E_{egd} > E_{sum}$ are then used to single out 256 element-windows (necessary for the spectrum analysis of the signal). This is done through the enlargement of the space of the selected 40-element windows by a further 216 elements (216 ms).

$$E_{egd} = E_{\min} + k * \left(E_{\max} - E_{\min}\right) \tag{2}$$

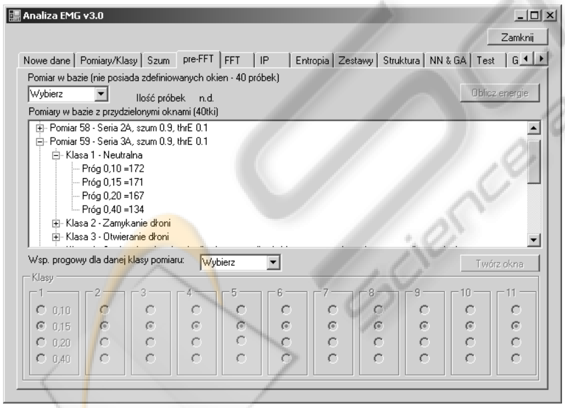

Figure 3: Signal usefulness analysis.

This stage is represented in Figure 3. In order to optimize this process, the application carries out a simulation of calculations simultaneously for a few values of the coefficient k ($k \in (0.1, \ldots 0.4)$). The operator can for each movement class select by means of the checkbox different values of his coefficient, which affects the number of the newly created 256-element windows.

The Windows determined in such a manner become the input vector for the feature extractor. As a result of the transformations for Fourier Transform we obtain the representation of the signal in the frequency domain (Figure 4).

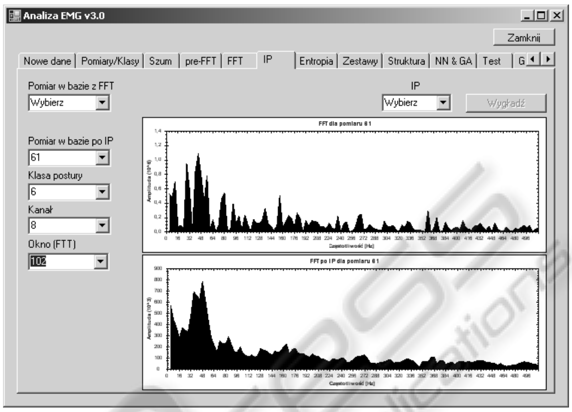

Figure 4: Exemplary FFT course (before and after averaging).

The spectrum pictures of the signal thus obtained are further subjected to the process of averaging of harmonics for the purpose of enhancing the degree of resemblance (data generalization) according to (3). The averaged values thus become the vector of signal features.

$$S[k] = \sum_{i=IPS}^{IPE} \frac{Y[i]}{IPE - IPS + 1}, \quad k = 0,1,\ldots, N-1 \tag{3}$$

In order to determine the features by means of Wavelet Transform, Mallat algorithm has been used (Mallat, 1989), which is used to obtain, among others, the vector of signal details which, after transformation is treated as the feature vector. The signal is filtered in accordance with:

$$c_m(n) = \sum_k l^*_{2n-k} c_{m-1}(\kappa) \tag{4}$$

$$d_m(n) = \sum_k h^*_{2n-k} c_{m-1}(\kappa) \tag{5}$$

According to the size of the windows (256 elements) that constitute the input vector that undergoes transformations, 6 levels of signal filtration had to be applied; each of the Mallat levels reduces by half the size of the input vector. Each of the Mallat levels is represented by number values that are the sum of absolute magnitudes of the detail vectors that arose earlier. The number of the features that thus arose (6 features) is smaller than the number of the assumed movement classes to be recognised. Thus a further 6 features had to be created in order for them to represent the dynamics of the changes in the recorded movement. This was done by summing up the real values respectively for each of the Mallat vectors that arose. In this way it was possible to obtain 12 values that represent the information contained in the signal as well as their approximations at each of the obtained levels of filtration.

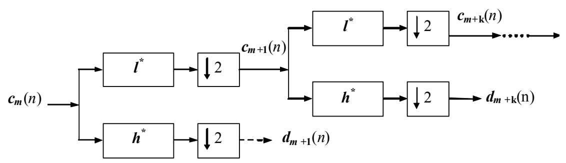

Figure 5: Signal filtration in compliance with Mallat algorithm.

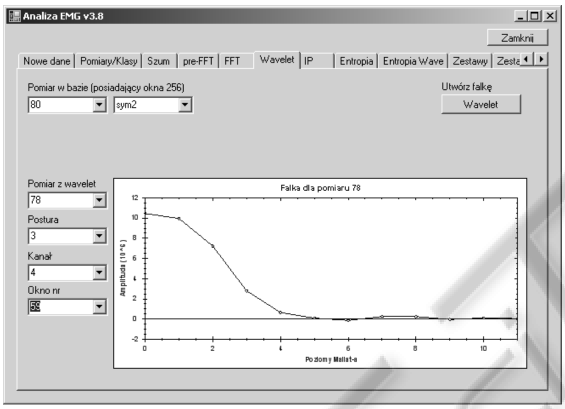

Figure 6: Exemplary Wavelet form.

3.2 Data Classification

The classification of the feature vector is of great importance in the presented approach. Due to a large number of movement classes and high recognition reliability (which is indispensable for the dexterity of the prosthesis) the classification process is a difficult problem. That is why, for convenience's sake, the classification process should be performed in an extensive manner – through many stages. In the presented research the method of multi-stage problem solution has been proposed, which is performed through the decision tree (DT). The structure of DT calls for: (a) the determination of its decision logic (structures and the assignment of classes to the terminal nodes); (b) determination of the subsets of features for indirect nodes; (c) determination of the decision making rules (algorithms of recognition in each indirect node). To build the DT based on Neural Network Tree (NNTree) solution (Zhao, 2001) the C4.5 algorithm was used, the one worked out by Quinlan (1993); it makes use of the entropy of information in the learning subset. Entropy in information theory is defined as the average amount of information that corresponds to a sign that symbolises an occurrence out of a certain set. The selection of the attribute is determined on the basis of the increase of the information.

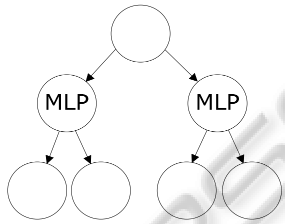

Figure 7: Exemplary NNTree.

The input vector that enables tree induction is the constituents: Fourier Transform (128 size vectors) or Wavelet Transform (12 size vectors) previously determined by information entropy of the set.

At this stage (Figure 8) it is possible to determine the data size that is to be transformed (single measurement, measurement grouping; specification of relevant signals).

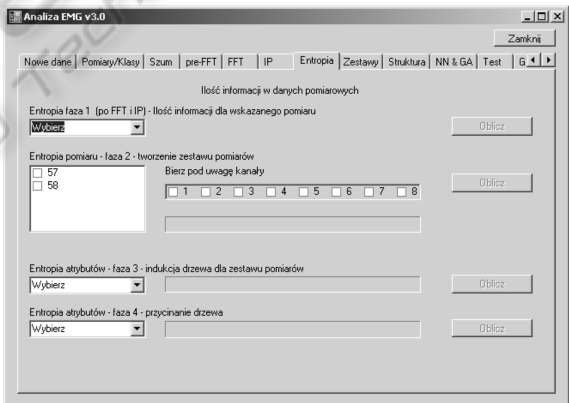

Figure 8: Entropy tab page.

Quinlan's method divides a given node into as many descending nodes, as many values there are in the most informative feature (constituent of the selected transform). The tree structure is made by recurring computation of the information increase coefficient for all available attributes at each recurring selection of the algorithm and the selection of the attribute for which this value is maximal (constituent of the selected transform). The recurring selection of the algorithm that makes up the tree structure ends the searching process of the input vector (FFT or DWT feature vector) provided that in a given sub-tree created by means of the recurring procedure a set of attributes represents one decision class. In this case a terminal mode is created that is marked with class label. The structure thus created has an input node, a root, and descendant nodes some of which (terminals) determine the decision class.

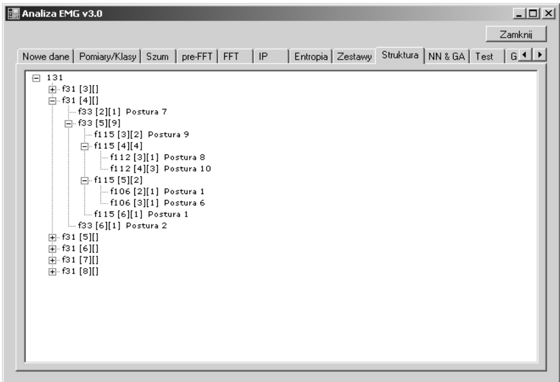

Figure 9: Exemplary decision tree.

To avoid too large a tree (and excessive matching), the pruning was used on the basis of the estimation of the significance of the difference of the classify-cation error for a given node and its sub-nodes. The algorithm estimates the probability of the decrease of the error occurrence and cuts off the divisions for which this probability does not exceed a given threshold value or provides identical results (similar results for the sub-nodes). The boundaries of the ranges that divide the space of the input vector (FFT or DWT) into the scopes of values that can be obtained were selected as a result of experiments so that their distribution was even for the whole span of the input. However, this method has a drawback; namely, new feature vectors that are to be classified can have values that cross the boundaries of two neighbouring scopes and represent different classes of hand movement. Therefore, the simple decision rules that consisted in comparing the new value with existing scopes were replaced with the decision making module i.e. MLP. On the basis of actual values from the database, *n* networks were trained (*n* – number of scopes in the MLP database $\{m_1...m_n\}$). Each of them ($MLP_1..MLP_n$) is responsible for the classification of the value from a given range ($m_1...m_n$). This solution introduces the genetic algorithm to create the MLP population that will allow for solving the problem of range classification.

The process is running until the intended classification error is obtained (the value falls within the range) or until the maximum iteration number is obtained (then the best configuration is returned – the least obtained error).

After the training process, the configuration and the weights of best MLP modules are directed to SQL database where they are assigned to given value ranges to be further used for classification process. The process consists in computing the attributes taken earlier from the input vector (EMG spectrum) in compliance with the decision scheme i.e. the tree structure. The decision rules are taken from the truth table. Additionally, the taken value is computed by means of relevant MLP_n module that simulates a given tree node (Figure 10). Thus we obtain the classic and neuron tree response. The activation of one of the descendant nodes brings about the recurring selection of another rule. The process is running until the final node (terminal) is reached. This node determines the decision class i.e. the type of identified posture.

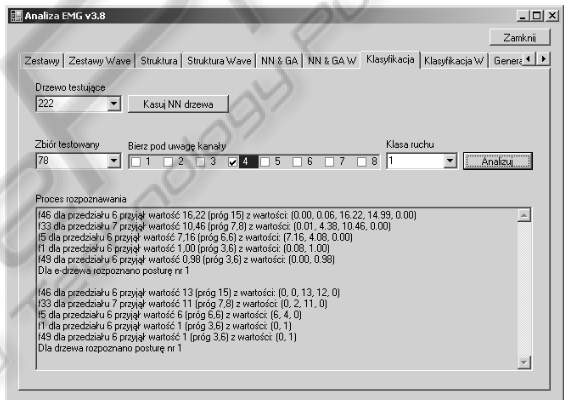

Figure 10: Classification process of the recorded signal.

4 EXPERIMENT AND OBTAINED RESULTS

The experiments were carried out on healthy persons by placing each time 6 electrodes on the skin of the forearm over relevant muscles.

Eleven movement classes were tested: 1. neutral; 2(3). flexion /extension of the hand digits; 4(5) pronation and supination of the forearm; 6(7) flexion / extension of the wrist; 8(9). flexion/ extension of the thumb; 10(11). flexion / extension of the fingers II-V.

For each class of movement the measurement lasted 7s and was preceded with a 5s break. In that way the discreet signals were obtained of the size 7.000 samples * 6 channels) per class (sampling

Table 1: Averaged classification errors of the tested movements for FFT input vector (Err_1-DT, Err_2-NNTree).

Class	1	2	3	4	5	6	7	8	9	10	11
Err_1 [%]	13	16	14	19	17	12	18	23	19	17	19
Err_2 [%]	9	14	14	17	9	10	13	21	12	11	14

Table 2: Averaged classification errors of the tested movements for DWT input vector (Err_1-DT, Err_2-NNTree).

Class	1	2	3	4	5	6	7	8	9	10	11
Err1 [%]	12	14	19	17	12	13	15	18	17	18	15
Err2 [%]	6	11	11	13	13	7	14	16	10	8	8

frequency 1 kHz). The data were located in the SQL database. The measurement data (1/3 of the signals selected at random) were used to generate the decision tree and MLPs. The remaining part of the set (2/3 of the signals selected at random) was assigned as a testing set.

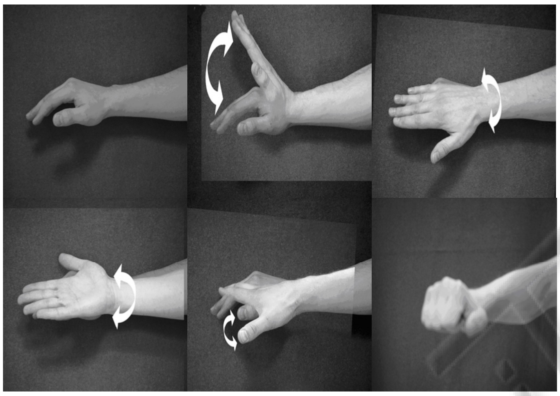

Figure 11: Tested movement classes.

The NNTree generated in this way gave an average recognition value equal to 87% (FFT) when the DT with classical nodes in turn gave a value equal to 83% (FFT). The detail results for tested movements are presented in Table1; were Err1 and Err2 represent the errors obtained respectively by DT and by NNTree methods for the FFT feature vectors. As we can see the best results were for classes 1, 5, 6 and 10.

In the case of DWT feature vectors an average recognition values were equal to 89% for NNTree and 85% for DT method. I this case the best results were for classes 1, 6, 10 and 11 (see: Table 2).

5 CONCLUSIONS

The tests with the presented "EMG Analysis" software are in the incipient stage. The conducted experiments aimed on principle at comparing the features extraction methods for EMG signals and their further classification. They prove the usefulness of the presented multistage analysis methods for the recognition of the decisions that control the manipulation and grasping movements of the artificial hand.

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