IDENTIFICATION OF HAND MOVEMENTS BASED ON MMG AND EMG SIGNALS

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Abstract: This paper proposes a methodology that analysis and classifies the EMG and MMG signals using neural networks to control prosthetic members. Finger motions discrimination is the key problem in this study. Thus the emphasis is put on myoelectric signal processing approaches in this paper. The EMG and MMG signals classification system was established using the LVQ neural network. The experimental results show a promising performance in classification of motions based on both EMG and MMG patterns.

1 INTRODUCTION

Biomedical signals means a set of electrical signals acquired from any organ that represents a physical variable of interest. These signals are normally a function of time and can be analysed in its amplitudes, frequency and phase. In the proposed method it is used two biomedical signals, electromyographic (EMG) and mechanomyographic (MMG) signals, to control the movement of prostheses.

Prosthesis systems for upper limb are mainly based on myoelectric control, recognizing EMG signals that occur during muscle contraction on the skin surface. Myoelectric control takes advantage of the fact that, after a hand amputation, great majority of the muscles that generate finger motion is left in the stump. The activity of these muscles still depends on the patient will, so biosignals that occur during it, can be used to control prosthesis motion (Asres, A., Dou, H. F., Zhou, Z. Y., Zhang, Y. L., and Zhu, S. C., 1996; Wołczowski, A., 2001).

In order to enhance functionality of such prosthesis another biosignal was researched. This signal is mechanical wave propagating in a contracting muscle (MMG) (Orizio, C., 1993). The nature and utility of MMG signals had already been studied namely in the control of a free-standing prosthetic hand (Goldenberg, M. S., Yack, H. J., Cerny F. J., and Burton, H. W., 1991; Ouamer, M., Boiteux, M., Petitjean, M., Travens, L., and Sal'es, A., 1999). A strategy to combine the MMG data and sensor fusion was proposed for the estimation and classification of muscle activity (Silva, J., Heim, W., and Chau, T., 2004). The fatigue of the biceps and brachioradialis muscles during sustained contraction was studied by (Tarata, M. T., 2003) using MMG signals. A linear classifier with a feature vector based on RMS power of the MMG signal was used to classify the finger movement in one of three possible groups (Grossman, A., Silva, J., and Chau, T., 2004).

In the proposed approach, an identification system will try to recognise a certain group of movements based on fusion of the mechanical and electrical signals (MMG and EMG signals) recorded on a patients arm. The features used are based on time and frequency histograms. The measurements were done on a specialized stand designed for such research.

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2 MEASUREMENT STAND

Measurement set was created specially for obtaining signals from patients arm. The configuration used in the measurement contained 6 input channels (Figure 1). Input channels from 1 to 3 were connected to the microphone sensors and input channels from 4 to 6 were connected to EMG differential electrodes.

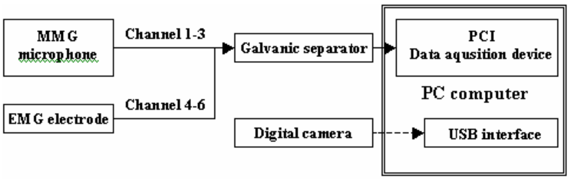

Figure 1: EMG and MMG acquisition system.

The microphone sensors are highly sensitive and are situated in a heavy brazen housing separating it from any external source of vibration. This microphone situated on the skin surface, records vibrations propagating in the tissue underneath it.

The microphone conditioning circuit filter out frequencies above 150 Hz as the frequency range of the mechanomyogram doesn't shows frequencies above this level (Orizio, C., 1993).

The EMG differential electrodes detect minimal potentials occurring on the skin over working muscles. It contains two contact poles situated 1 cm away from each other and amplifies only the difference between the two readings. Frequency of the electromyogram goes into range between 20-400 Hz (Krysztoforski, K. and Wołczowski A., 2005).

A digital camera can be used as an addition to the stand as feedback information. It allows extracting data from specific stages of movement.

3 METHODOLOGY

In the experiment sensor were attached to the patient's right arm. One set of microphone and electrode was positioned at the top of the forearm near the elbow. The second and the third pairs of microphone and electrode were positioned at the bottom of the forearm near the elbow and near the wrist, respectively. Table 1 shows the channels used in the acquisition of EMG and MMG signals.

During the measurements patient was repeating the same set of movements with various speeds and duration of the muscle contraction. Those movements were:

I – Hand closing;
II – Pointing with one finger;
III –Pointing with two fingers;
IV – Wrist flexion – down;
V – Wrist flexion – up;
VI – Pronation / suplination;
VII – Whole hand movement left / right;

All measurements were made with 1kHz probing density and lasted 5 sec. In each 5 second measurement the move was repeated two or three times.

Table 1: Channels used in the acquisition systems.

Sensor	Channel
MMG microphone	1
EMG electrode	4
MMG microphone	2
EMG electrode	5
MMG microphone	3
EMG electrode	6

3.1 Data Visualisation and Analysis

In order to create input for a classification system the data gathered during the measurements had to be analysed in search of the signal features. In figure 2 is shown typical MMG and EMG signals obtained during 5 seconds in channel 4. It can be seen that during these interval of time, one type of movement was repeated three times during the presented tests.

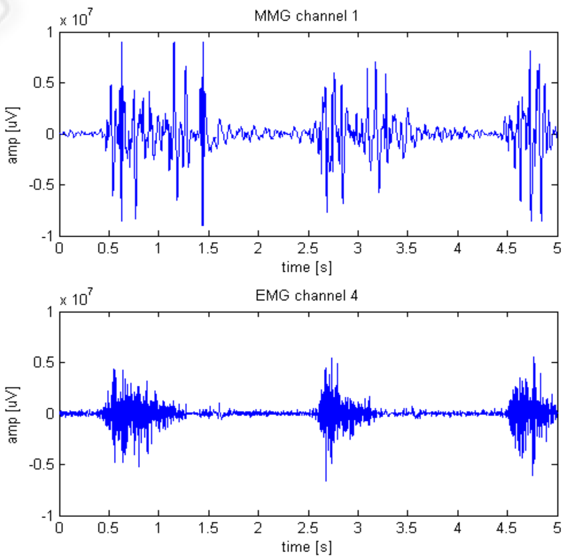

Figure 2: EMG and MMG signals.

The signal features were observed on a 3D histogram containing information in both time and frequency domains using Short Time Fourier Transform (STFT). An example of such histogram is shown on figures 3 and 4, for MMG and EMG signals obtained from one movement, respectively.

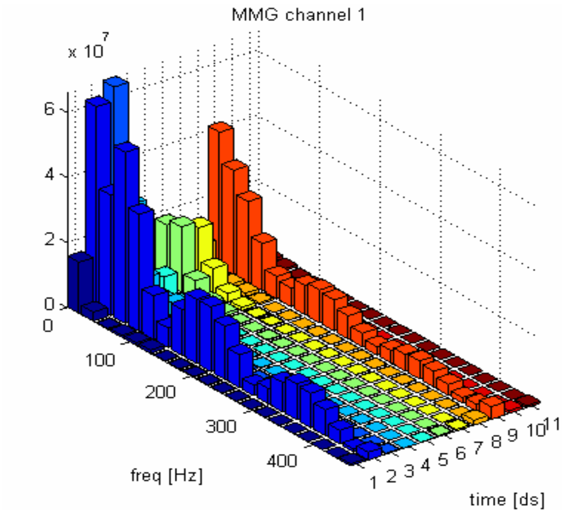

Figure 3: MMG frequency spectral density histogram.

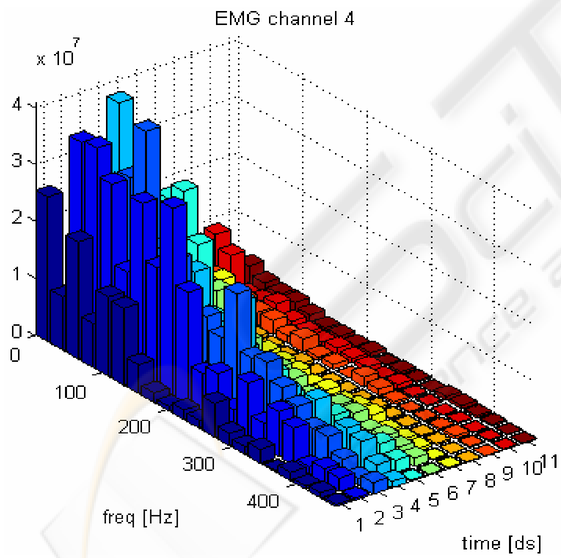

Figure 4: EMG frequency spectral density histogram.

It can be deducted from the histograms analysis, for every movement, that the MMG histogram has two peeks – in the beginning and at the end of the movement, whereas in the middle of the muscle activation spectral density is relatively low.

In the EMG histogram the signal is strongest while the muscle is kept contracted.

3.2 Feature Extraction

In the feature selection stage, the same number of features for each EMG and MMG channel are used.

The selection of the elements of the feature input vector has to take advantage of the knowledge about the signal features in the time and frequency domain.

Therefore the selection of the input vector elements is based on the time/frequency histograms. The proposed algorithm for selecting points is divided in five steps:

1- Extracting the movement part from every channel of 5s measurement record (Figure 5);

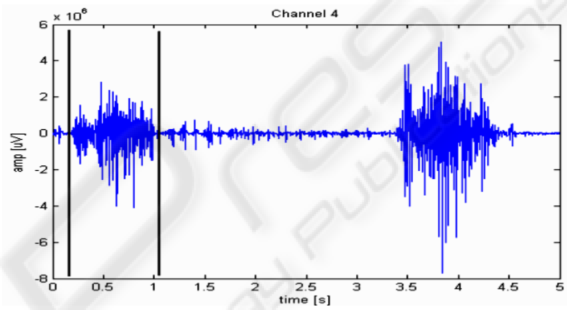

Figure 5: EMG signal obtained in channel 4.

2- Application of the STFT in the beginning (0.3t, where t is the movement time span), in the middle (0.5 t) and at the end (0.7 t) of the extracted movement;

3- In the frequency domain, in three specified moments of time, a set of n points is obtained (from the frequency range adequate to the channel type) (Figure 6).

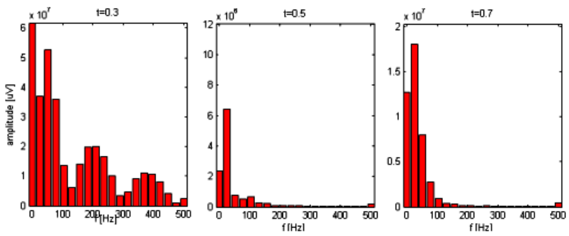

Figure 6: Frequency components in EMG signal.

4- Step 2 and 3 is repeated for every channel;

5- Normalization of the signals amplitude.

This procedure allows to create input vectors with an adjustable size. The minimum number of elements in the feature vector using 6 channels is 18. The minimum structure of these feature vector used as an input in the classifier based on a neural network is given by:

$$\left[A_{t1f}^{ch1}\ A_{t2f}^{ch1}\ A_{t3f}^{ch1} \ldots A_{t1f}^{ch6}\ A_{t2f}^{ch6}\ A_{t3f}^{ch6} \right] \quad (1)$$

The element A_{t1f}^{ch1} represents the signal amplitude in the channel 1 for the instant of time *t1* in the frequency *f*.

The minimum structure of the feature vector using only three channels (EMG or MMG) as 9 elements and is given by:

$$\left[A_{t1f}^{ch1}\ A_{t2f}^{ch1}\ A_{t3f}^{ch1} \ldots A_{t1f}^{ch3}\ A_{t2f}^{ch3}\ A_{t3f}^{ch3} \right] \quad (2)$$

3.3 Classification Method

The electromyographic and mechanomyographic signals are classified using the Learning Vector Quantization (LVQ) neural network. The LVQ network is a mutation of self-organizing Kohonen's maps. Unlike standard neural networks, it contains usually only one layer of neurons. Each neuron is subscribed to one class (Figure 7). The [x_1, x_2, …, x_n] is the feature vector and [y_1, y_2, …, y_n] represents each output movement. This kind of network proved to be efficient in biosignal recognition problem in previous research conducted by the authors (Wolczowski A. 2001, Krysztoforski, K. and Wołczowski A., 2005).

Usually there is more than one neuron for each class. Each neuron has its weight vector containing as many elements as data input (Kohonen, Teuvo K., 1995). During the teaching of the network, in every iteration, for each data vector a winning neuron is being settled based on the closeness (in Euclid's metrics) of the neuron weights to the data vector (Kohonen, Teuvo K., 1995).

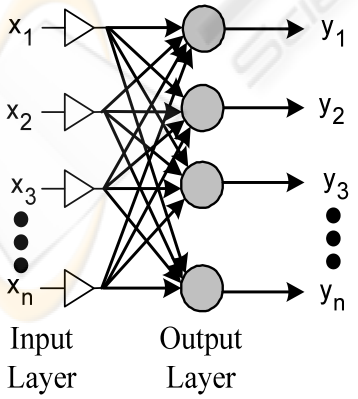

Figure 7: Neural Network architecture.

If the winning neuron represents the same class as the input vector, its weights are being changed to be even closer to this input. If the classes are different the weights are being pushed away.

The basic update algorithm is:

→ If **x** and $\mathbf{m_c}$ represent the same class then

$$\mathbf{m}_c(t+1) = \mathbf{m}_c(t) + \alpha(t)[\mathbf{x}(t) - \mathbf{m}_c(t)] \quad (3)$$

→ if **x** and $\mathbf{m_c}$ represent different classes then

$$\mathbf{m}_c(t+1) = \mathbf{m}_c(t) - \alpha(t)[\mathbf{x}(t) - \mathbf{m}_c(t)] \quad (4)$$

-> from i ≠ c,

$$\mathbf{m}_i(t+1) = \mathbf{m}_i(t) \quad (5)$$

where **c** is the index of the winning neuron and $\alpha(t)$ is a teaching factor ($0 < \alpha(t) < 1$).

There is a different teaching factor for each neuron in the system and adapts during the process of teaching, starting from the initial value of 0.5 according with the following expression:

$$\alpha_c(t) = \frac{\alpha_c(t-1)}{1 + s(t)\alpha_c(t-1)} \quad (6)$$

Where:

$$s(t) = \begin{cases} 1, & \textit{if classification is correct}; \\ -1, & \textit{otherwise.} \end{cases} \quad (7)$$

An algorithm for handling unused neurons in every teaching epoch was applied.

4 EXPERIMENTAL RESULTS

Experiments were carried out in laboratory, and EMG and MMG signals were captured and recorded simultaneously during the motion of the subject's hand (Figure 8). The next step was extracting the features according to the proposed algorithm. Two sets of vectors (containing 36 or 90 element) were created. The vectors were divided into two groups – one for teaching and the other for testing, each one contained 81 vectors.

In each test the neural network was trained with 200 epochs using vectors from the teaching group. Training was followed by the classification process preformed on the vectors from the test group. The same procedure was repeated using vectors based only on EMG signal features and vectors based only on MMG signal features in order to determine how useful is the combination of both biomedical signals.

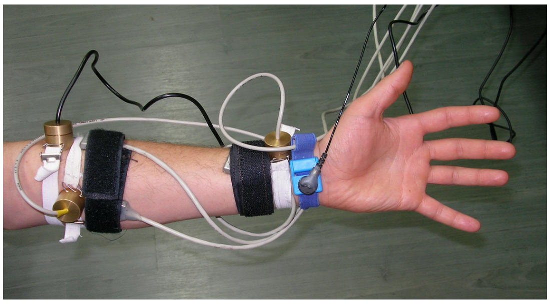

Figure 8: Patient's arm with attached sensors.

Figures 9 and 10, show the neural network error during the training stage when the input vector size is 36 and 90, respectively. The training error, for each epoch, is obtained by the mean value of the Euclidean distance between the current teaching example and the winning neuron.

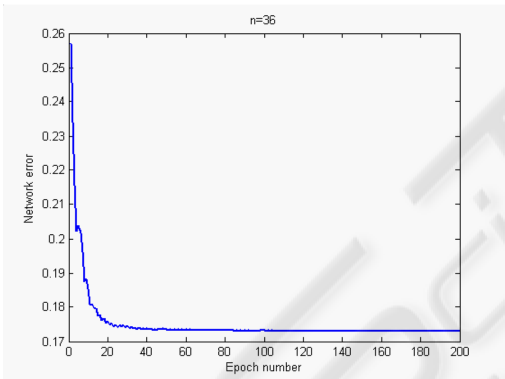

Figure 9: Training error for a vector size of 36.

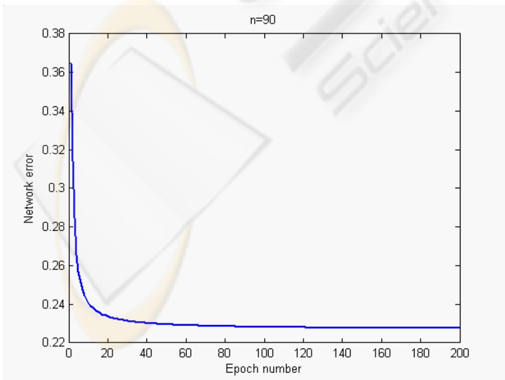

Figure 10: Training error for a vector size of 90.

Tables 2-3 and Table 4, show the results of the test vectors classification with the input vector size of 18 and 36, respectively. In the first row of each table it is represented the number of class movement indicated by the classification process. In the first column of each table are represented the class movements of the examples introduced in to the neural network. The test examples classified correctly are in bold.

Table 2: Classification based on MMG signals.

	1	2	3	4	5	6	7
1	**10**	0	2	0	0	0	0
2	2	**13**	3	0	0	0	0
3	0	0	**8**	0	1	0	0
4	0	0	0	**10**	0	0	0
5	0	0	0	0	**11**	0	3
6	0	0	0	0	0	**8**	1
7	1	0	0	0	0	2	**6**

Table 3: Classification based on EMG signals.

	1	2	3	4	5	6	7
1	**12**	0	1	0	0	0	0
2	0	**12**	1	0	0	0	0
3	1	0	**11**	0	0	0	1
4	0	0	0	**10**	0	0	0
5	0	0	0	0	**11**	0	0
6	0	0	0	0	0	**10**	1
7	0	1	0	0	1	0	**8**

Table 4: Classification based on EMG and MMG signals.

	1	2	3	4	5	6	7
1	**12**	0	1	0	0	0	0
2	0	**13**	1	0	0	0	0
3	1	0	**11**	0	0	0	0
4	0	0	0	**10**	0	0	0
5	0	0	0	0	**11**	0	0
6	0	0	0	0	0	**10**	1
7	0	0	0	0	1	0	**9**

The classification error obtained for the testing vectors group using only information form MMG channels was 18.52%. The error obtained using only the EMG signals in the input feature vectors was 8.64%. Finally, when features from both the EMG and MMG signals were used in the input vector, the classification error decreased to 6.17%.

The same tests were done using an input vectors with 45 and 90 elements. The results of the classification process are shown in Tables 5-6 and Table 7, respectively. The classification error obtained using only MMG signal features was 24.7%. The error obtained using only the EMG signals in the input feature vector was 2.46%. When it is combined in the input vector, the features from both the EMG and MMG signals, the classification error decreased to 1.24%.

Table 5: Classification based on MMG signals.

	1	2	3	4	5	6	7
1	**9**	0	2	0	0	0	0
2	1	**9**	2	0	1	0	0
3	3	4	**9**	0	0	0	0
4	0	0	0	**10**	1	0	2
5	0	0	0	0	**10**	1	0
6	0	0	0	0	0	**7**	1
7	0	0	0	0	0	2	**7**

Table 6: Classification based on EMG signals.

	1	2	3	4	5	6	7
1	**13**	0	1	0	0	0	0
2	0	**13**	0	0	0	0	0
3	0	0	**12**	0	0	0	1
4	0	0	0	**10**	0	0	0
5	0	0	0	0	**12**	0	0
6	0	0	0	0	0	**10**	0
7	0	0	0	0	0	0	**9**

Table 7: Classification based on MMG and EMG signals.

	1	2	3	4	5	6	7
1	**13**	0	1	0	0	0	0
2	0	**13**	0	0	0	0	0
3	0	0	**12**	0	0	0	0
4	0	0	0	**10**	0	0	0
5	0	0	0	0	**12**	0	0
6	0	0	0	0	0	**10**	0
7	0	0	0	0	0	0	**10**

5 CONCLUSIONS

The results obtained during the experiment imply that efficient identifying hand movements based only on one MMG sensor is very difficult. Especially the first three movements are being confused during the identification process. The reason for such error is because those movements are caused by similar muscles and therefore sounds propagating during those movements are much alike.

The EMG based identification system gives much greater accuracy. The neural network taught with EMG based data badly recognizes only a small percent of test examples. Using the information obtained from both mechanomyogram and electromyogram improves results of the EMG-based recognition. Therefore it can be concluded that the mechanomyographic sensors can be used as a enhancement to a EMG prosthesis system improving the accuracy of identification and count of the supported range of movements. LVQ network proved produced sufficient and satisfactory recognition ratio, therefore proving its usefulness in the biosignal-based prosthesis control problem. Further improvement could be achieved by applying more complex neural network architectures in the recognition process and also by modifying the feature extraction algorithm. Those are the key areas for future investigation of the problem.

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