Initial Analysis of the EEG Signal Processing Methods for Studying Correlations between Muscle and Brain Activity

Helena Valentová and Jan Havlík

Department of Circuit Theory
Faculty of Electrical Engineering
Czech Technical University in Prague
Technická 2, CZ-16627 Prague 6
xhavlikj@fel.cvut.cz

Abstract. The paper presents an analysis of EEG signal processing methods for studying correlations between human muscle and brain activity. The main task of this work is to design the methods of EEG signal processing and to verify them on artificial and real signals. The paper introduces methods of EEG processing in time and frequency domain.

Keywords: EEG, signal processing, muscle activity

1 Introduction

The paper presents an initial study of electroencephalographic (EEG) signal processing methods for the analysis of correlation between human muscle and brain activity.

The correlation between muscle and brain activity is one of the most interesting tasks in current biomedical engineering. As it is commonly known the muscle activity is controlled by the brain. It means the muscle activity has to correlate with brain activity. Unfortunately the brain activity is very complex and identifying of the activity respective to the muscle activity is not easy.

The correlation between brain and muscle activity was proved in many previous studies. The frequent approach is finding the coherence between brain activity and EMG (electromyogram, the record of muscle activity) signal. The brain activity is usually represented by the EEG (electroencephalogram, the electrical record of brain activity), for example [1], [2] and [3], but some studies presents the research of correlations between muscle activity and brain activity represented by MEG (magnetoencephalographic) signals [4].

The information about relationship between brain and muscle activity could help understanding how the brain controls the muscles and also could help recognizing first stages of many movement disorders (e.g. Parkinson disease and neuropathy).

Most of the previous studies concerned recognizing human body movements from EEG signals using two types of movements (e.g. the right index finger distal movement and right shoulder proximal movement [5]).

The main goal of current research is to assign typical changes of EEG signals to the type of thumb motion. The thumb movements are not reduced to two types of motion for this study.

2 Experiment

Brain activity is represented by the EEG signals, the muscle activity is represented by the parameters of the thumb trajectory.

During the experiment a measured person seats in an upright position. The arm with observed thumb is supported by an armrest. The thumb moves between 3 positions – stationary states. Each movement is triggered by the synchronization pulse. The period of pulses is 6 ± 1 seconds. About 20 % of period is reserved for movement, the rest 80 % of period is the stay on the position.

The motions are sensed using a pair of standard DV camcorders. The sensed motions are recorded to a tape and stored to a PC after the experiment. The thumb trajectory is parameterized based on the processing of video sequences.

The EEG signals and video sequences are synchronized using the common synchronization signal.

3 Methods

The main task of this study is to separate blocks from EEG signal with the brain activity sensed during the finger motion and to classify the signals to the

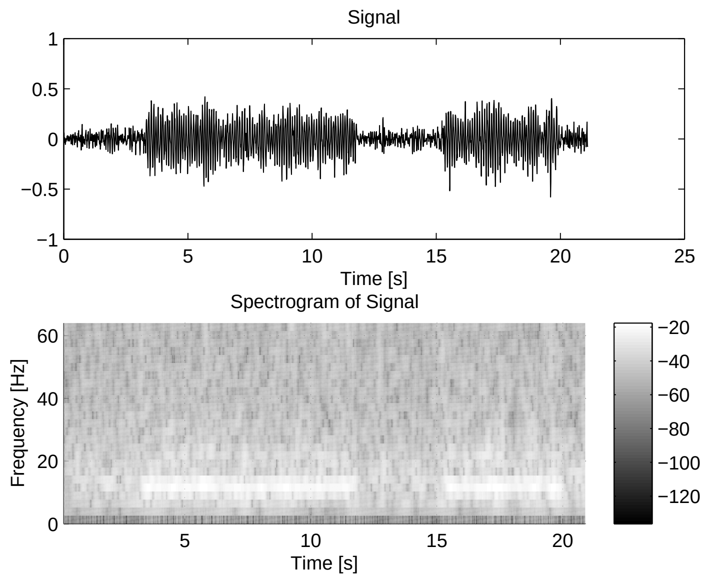

Fig. 1. Sample signal

classes – separate class for one type of motion. It is evident, that the EEG signals reflect not only intentional motions, but also all vital functions, artifacts from eye motions, spontaneous activity etc. In fact the effective signal has lower amplitude than the signal background. Unfortunately it means that it is very complicated to find the effective signal.

For these reasons the main idea is to use similar methods as methods for processing of evoked potentials. The methods are based on two main facts. The first one is that the EEG signal background is uncorrelated with the effective signal and the second one is that the effective signal is the same or very similar for each realization of motion. With this precondition the effective signal could be mined using the averaging methods. The methods assumes many realizations of each type of motion and the corresponding EEG signal.

3.1 Averaging in Time Domain

The easiest method is averaging in the time domain. Let's have N realizations of signal $s_n[t]$, where $n = 1 \dots N$ is the index of realization, for each type of motion. The effective signal could be computed as simple average

$$\overline{s}[t] = \frac{1}{N} \sum_{n=1}^{N} s_n[t]. \quad (1)$$

This method is very simple, with very low computational demands, but the method is very sensitive to the phase of signal. It means the effective signal has to start in the same point of each processed segment.

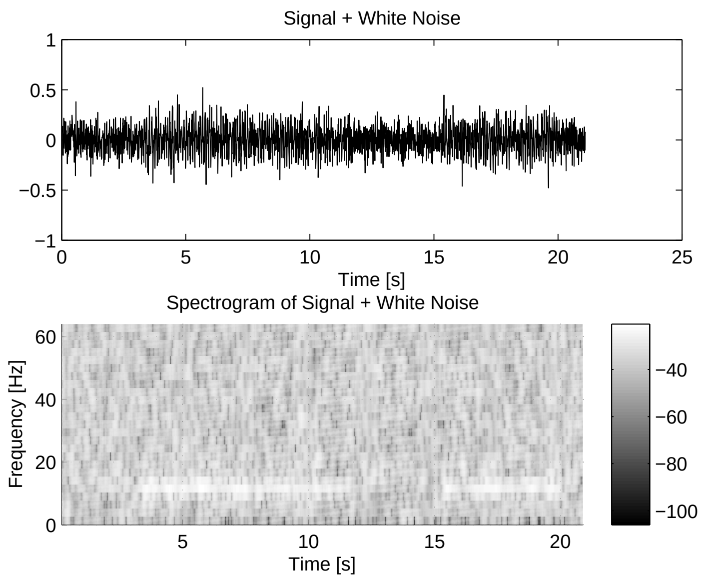

Fig. 2. Signal with white noise

3.2 Averaging in Frequency Domain

Another method is averaging the signal in the frequency domain using the Power Spectral Density (PSD). Let's have the same signal $s_n[t]$ as in the previous example divided to I segments with length J and the respective short time Fourier transform $S_n[i, j]$, where $i = 1 \ldots I$ and $j = 1 \ldots J$. The PSD matrix $P_n[i, j]$ of signal $s_n[t]$ is defined as $P_n[i, j] = |S_n[i, j]|^2$. The PSD of effective signal could be computed as the average

$$\overline{P}[i, j] = \frac{1}{N} \sum_{n=1}^{N} P_n[i, j]. \tag{2}$$

The method is resistant to the shift of signal, but it has higher computational demands than averaging in time domain.

4 Evaluation

4.1 Evaluation on Artificial Signals

The EEG signal of eye movements with length more than 20 seconds were used for preparing artificial signal. The time behaviour and the spectrogram of the clear signal is shown in figure 1 (sample frequency $f_s = 128\,\text{Hz}$).

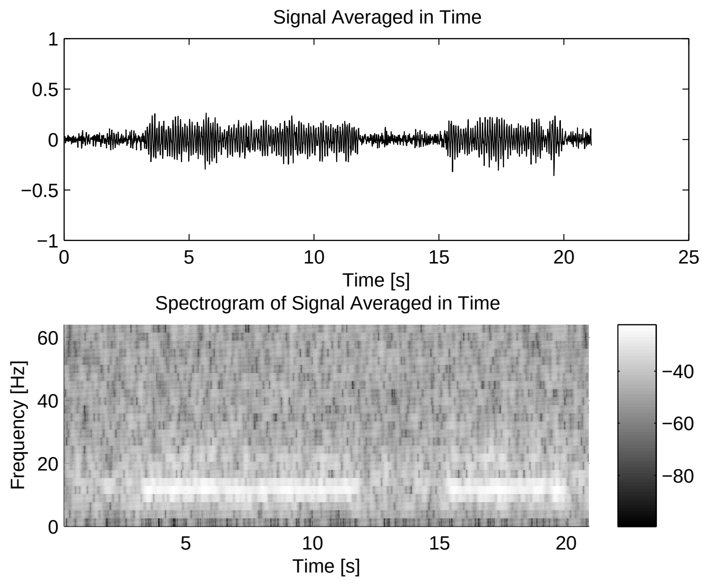

Fig. 3. Averaging in time domain

$N = 50$ realizations of the artificial signal were used for the tests. Each realization was produced by mixing of clear signal with white noise ($SNR = -5$ dB). Typical realization of signal with noise is shown in figure 2.

The averaged signal and averaged PSD are shown in figures 3 and 4. All the algorithms were implemented in the MATLAB programming environment.

4.2 Evaluation on Real Signals

The methods were also evaluated on the real dataset. The signals were acquired during two experiments. The EEG signals were measured using the $10 - 20$ electrodes system with the sample frequency $f_s = 250$ Hz. The signal from sensomotoric area (electrode C3) was processed.

Each experiment had the length of about 10 min. It means that the signal database includes about 100 realizations of finger motions in one experiment. The signals were divided to the segments with respect to proper beginning of the motion. Information about the beginning of motions was obtained manually from the video sequences. Each segment was started 0.5 s before the motion start and finished 1.5 s after the motion start. It guarantees sufficient length of signal both before and after the motion.

Because the thumb moves between 3 stationary states in the experiment, the number of observed types of motions were 6 (from each position to any other in both directions). It means that the database includes about 30 realizations of each type.

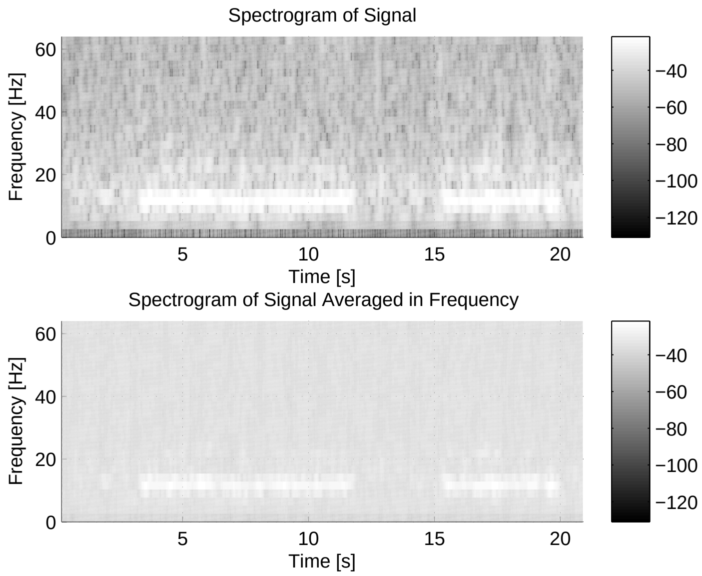

Fig. 4. Averaging in frequency domain

The results of evaluation on the real data are very preliminary. It could be supposed that the weak results have several main reasons.

The first one is very small number of realizations in database. It is necessary to make additional experiment for the proper evaluation in real conditions. The second one is uncertainty in determination of motion starts. It is principal problem, but especially for averaging in time domain it is evident that each small shift in determination of motion start could have great impact to final averaged signal.

Moreover, some previous studies showed that for some persons the coherence between brain and muscle activity is very unrecognizable. It is necessary to make the experiments with more than one measured person.

5 Conclusion

The two averaging methods were designed, implemented and evaluated during the initial study of EEG signal processing methods. The usability of the methods was evaluated both on artificial and real signals.

The test on artificial signals produced satisfactory results, but the test on real signals showed many problems. The most serious one is the requirement of great number of signal realizations. That means more experiments have to be performed for better evaluation of methods applied to real signal database.

Using the results from artificial signals it could be assumed that the methods are usable for finding the correlations between human muscle and brain activity.

Acknowledgement

This work has been supported by the research program No. MSM 6840770012 of the Czech Technical University in Prague (sponsored by the Ministry of Education, Youth and Sports of the Czech Republic).

References

1. R. Bortel and P. Sovka. EEG–EMG coherence enhancement. *Signal Processing*, 86:1737 – 1751, 2006.
2. S. Salenius, R. Salmelin, C. Neuper, G. Pfurtscheller, and R. Hari. Human cortical 40 Hz rhytm is closely related to EMG rhythmicity. *Neuroscience Letters*, 213(2):75 – 78, 1996.
3. Tuncel. D., A. Dizibuyuk, and M. K. Kiymik. Time frequency based coherence analysis between EEG and EMG activities in fatigue duration. *Journal of Medical Systems*, 34(2):131 – 138, 2010.
4. S. Salenius, K. Portin, M. Kajola, R. Salmelin, and R. Hari. Cortical control of human motoneuron firing during isometric contraction. *Journal of Neurophysiology*, 77(6):3401 – 3405, 1997.
5. J. Šťastný, P. Sovka, and A. Stančák. EEG signals classification: Introduction to the problem. *Radioengineering*, 12(3):51 – 55, 2003.
6. Jan Uhlíř and Pavel Sovka. *Digital Signal Processing (in Czech)*. Vydavatelství ČVUT, Praha, 2002.