EEG Power Spectrum Analysis During Mental Task Performance

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Abstract: *A power spectrum analysis of electroencephalograms (EEG) for brain computer interface (BCI), which uses pattern recognition technique, is made. A study of changes of the power spectrum in the range 8-13 Hz along the time during "inactive state" and "imaginary rotation" mental tasks' performance is made. The noticed regularities will be used to rise the quality of the EEG excerpts used for mental tasks' selection and to improve BCI's work.*
Key words: *BCI, EEG data analysis, mental task, MMI*

INTRODUCTION

A recent review on BCI defines a Brain-Computer Interface as a system for controlling a device, e.g. computer, wheelchair or a neuroprosthesis by human intentions, which does not depend on the brain's normal output pathways of peripheral nerves and muscles. BCI should be able to detect the user's wishes and commands while the user remains silent and immobilized. In order to do this, the brain must be monitored.

Almost all of the studies are based on electroencephalogram (EEG) recorded from the scalp as a noninvasive and easy to use method, which does not require heavy and complicated equipment. The EEG is measured and sampled, particular preprocessing and feature extraction methods are applied to EEG samples of certain length. Some BCI are based on the identification of mental tasks. Generated brain potentials during the performance of various mental tasks characterize the specific states of the brain. These tasks activate various cortex areas and produce different EEG rhythms. Using a particular type of a classifier (artificial neuron net (ANN)), task-specific EEG signals (patterns) from the EEG samples with a certain level of accuracy are detected. The method is known as pattern recognition.

EEG is the spontaneous electrical activity of the billions of nerve cells, the connections between them in the brain cortex and the structures just below it [9]. As the phrase "spontaneous brain activity" implies, this activity goes on continuously in the living individual. No cerebral activity can be detected from a patient with complete cerebral death. The amplitude of the EEG is about 100 μV when measured on the scalp, and about 1-2 mV when measured on the surface of the brain. The bandwidth of this signal is from under 1 Hz to about 50 Hz. Until the brain itself is capable to repeat exactly a particular mental task, the patterns emitted by the brain that could be recorded include the electrical activity of various groups of neurons and strong differs during every repetition of the task. As a result EEG, corresponding to a particular mental task differs every time. The science and technologies' development changed this situation. Dependencies between EEG rhythms and real or imaginary movements were demonstrated as much as dependencies between EEG and mental tasks [6, 8, 12]. Fast modern computers are able to perform complicated multichannel EEG processing [13] that raised the level of recognition.

Still many specific problems exists: EEG recording produces a lot of noise, BCIs are very susceptible to artefacts [10], more EEG effort is necessary to determine where and how electrophysiological states correlate with mental states, and how this varies in different subjects.

A stage of developing of BCI is a mental task EEG feature extraction. Then after some pre-processing of the data, the classifier could be trained. It is important to find the appropriate mental tasks and perform them such a way, to achieve as high as possible data quality.

In this study an analysis changes of the power along the time of a task with an expressive pattern is analysed.

EXPERIMENT

As a base of the study is the EEG database, made in Delft University of Technology, Delft, The Netherlands in 2005. Later some additional records were done. For the goal of the project, EEG records were made during the performance of different mental tasks. In advance the tasks were chosen to evoke brain activity in different parts of the brain. The database contents records of more than 40 sessions around 40 minutes each. Together with the equipment preparation (putting an electro technical gel in every electrode and electrodes resistance control) every session took around 2 hours. To achieve higher authenticity of the data only one session per day was recorded for every subject. The brain activity in α- and μ-ranges (8 – 13 Hz) [9] was studied. All the EEG were recorded without any biofeedback – the subject performed the mental task without having information about the result.

As a data acquisition system "Truscan 32 EEG" including EEG cap, EEG amplifier and EEG adapter [14], was used in the experiments. The needed low resistance of the contact electrode - skin was improved by the use of an electro technical gel and was controlled during the recording process.

InterBase database management system (DBMS) was used. MATLAB was used as a data processing application.

After a preliminary comparison analysis between the mental tasks, table 1, was made and the features were extracted it was interesting how these features keep/change along the time.

Table 1

Compared tasks	Changes in rhythm	Subject	Scalp location at [Hz]
Inactive vs. Imaginary Rotation	Mu, Alpha	1, 2	P3, P4 – 10

In this paper only a study of "inactive state", task 1 and "imaginary rotation", task 8 is described. The inactive state was defined as a subject's state of a rest. The subject is relaxed and should not think of anything. A thought about anything – an object or a process - could exercise an influence on the brain rhythms of interest. The inactive subject state was chosen as a "baseline task" – the task that will be compared with all other tasks and the task that will be performed between every other task during BCIs work. The "imaginary rotation" was chosen, because it has a well-expressed and well spatially defined EEG pattern and could easy be studied. First 5 s the subject is looking to the image of a cube on the monitor. After the image disappears he started to imagine the cube moving (rotated) in an arbitrary direction. The mental activity reduces α- brain rhythm in the prefrontal cortex (FP1 and FP2 channels) and μ- brain rhythm in the parietal cortex (P3 and P4 channels) [9].

For μ-rhythm study the Gabor transform (Short time Fourier transform) was used. With this approach Fourier Transform is applied to time-evolving windows of one second of data (256 samples) smoothed with an appropriate window function (to reduce the spectral leakage) [1, 5, 7, 11]. Then, the evolution of the frequencies can be followed and the stationarity requirement is partially satisfied by considering the signals to be stationary in the order of the window length. In other words - the procedure consists in breaking the signal in small, overlapping time segments, multiplying to a Hamming window and then in applying a Fourier Transform to the successive segments. To smooth the shape, a moving average filter between equal frequencies in neighbor segments was used. Typical plots for both tasks are given on fig. 1, 2 and 3. Each graph represents the change of the power spectrum during the task performance for a period of 25 s.

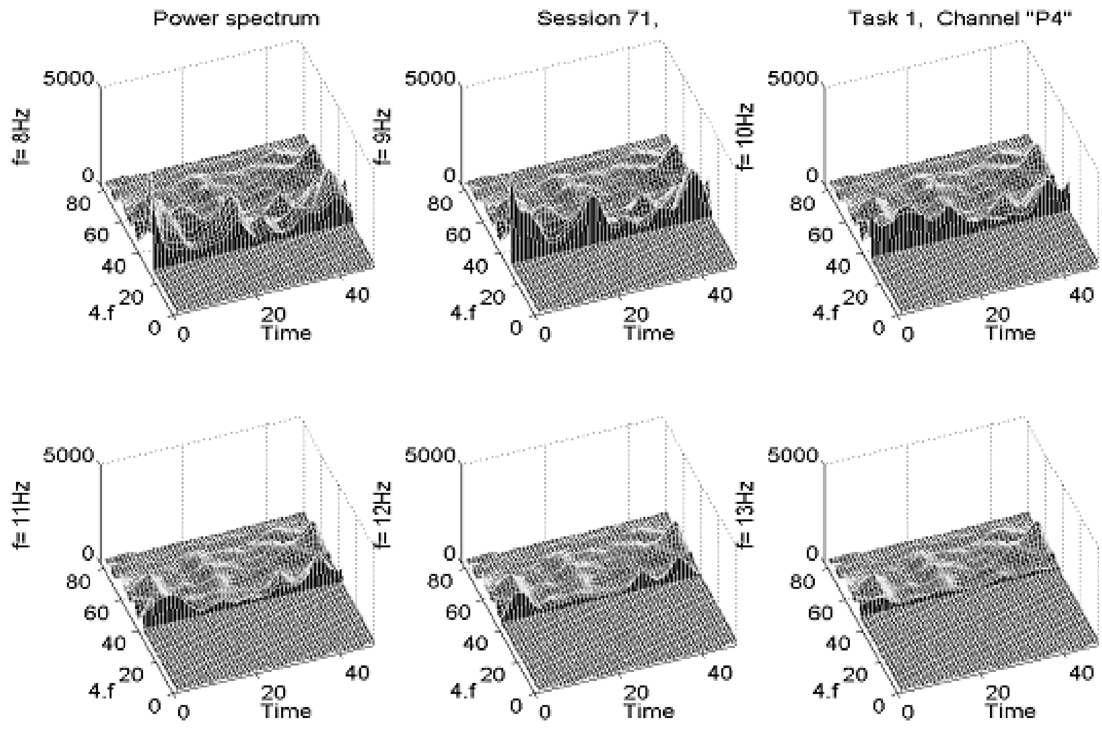

Fig. 1. EEG power spectrum during the task 1 - an inactive state of the subject

ANALYSIS AND CONCLUSIONS

During the preliminary selection of the mental tasks it was found that the imaginary rotation task has its biggest changes for μ-rhythm at 10 Hz, so the power of this frequency is studied here. For both studied tasks following conclusions were made: An inactive state is comparatively easy and quickly to achieve. It is most clear expressed during first 8-10 s of the task performance – see the high level of the power on the graph for 10 Hz on fig. 1 (pay attention that the scale for the frequency is 4.f). Later until "relaxing", the subject started unintentionally think about something, which leads to reduction or unsteady power spectrum (when from time to time the subject is aware that he is thinking and tries to spread his attention, to "think about nothing". This could be seen as decreasing and increasing of the power of 10 Hz at the end of the 25 s period on fig. 1.

During the performance of "imaginary rotation" the dependency is similar. First 10 seconds of the performance the subject has his attention concentrated on the task and the decreasing of the power is clear expressed – see 10 Hz graph on fig. 2. Later he unintentionally decreases his attention and as a result power's reducing is poor.

To check this statement new records with a biofeedback were made. The biofeedback was in the form of a bar on the computer screen, which length was proportional to the power of the most sensitive frequency (10 Hz in this case) in the range. A graph of one of the measurements is on fig. 3. The biofeedback information keeps the subjects attention and the reduction of the μ-rhythm is more stable during the whole time period.

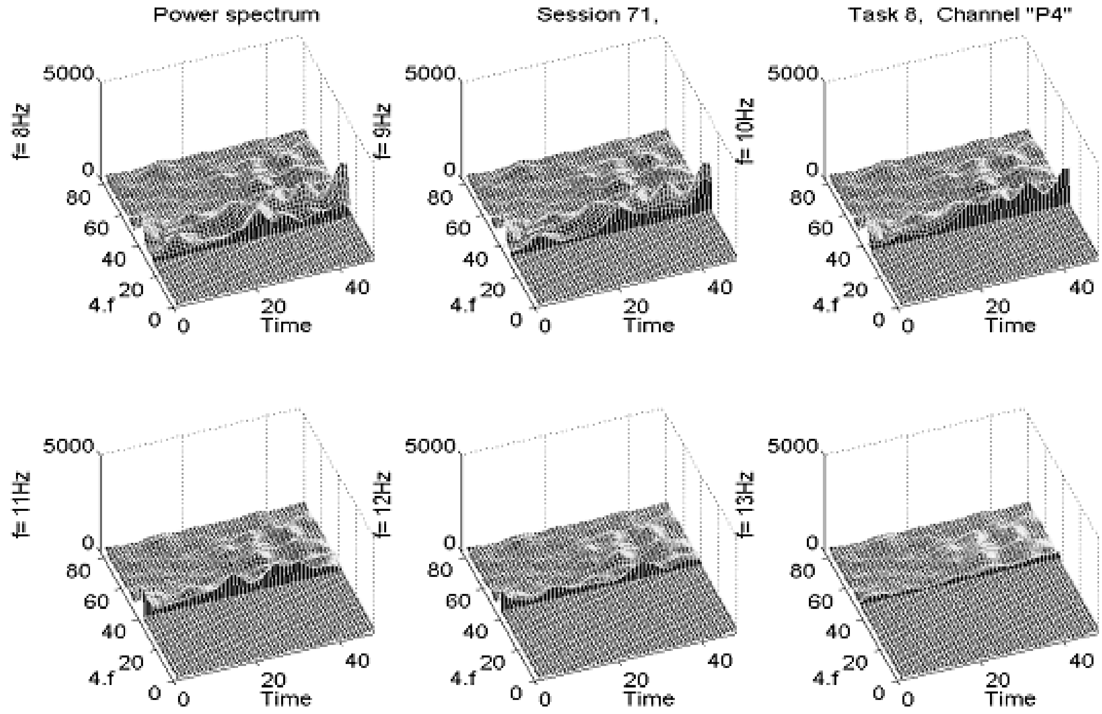

Fig. 2. EEG power spectrum during task 8 – imaginary rotation

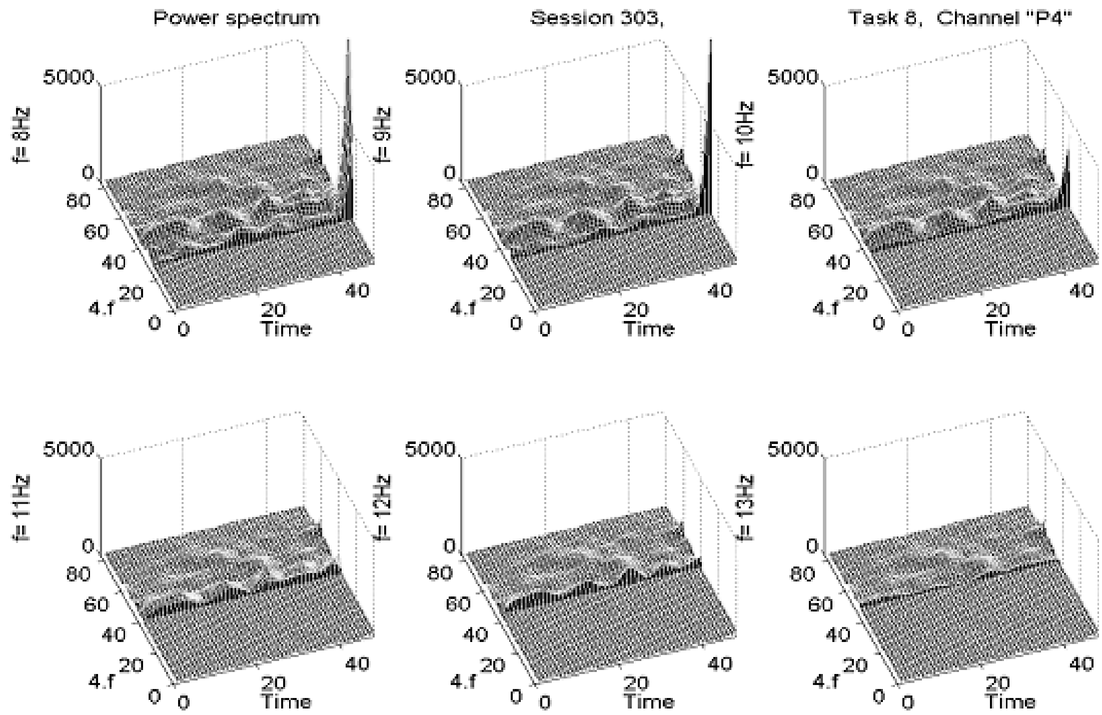

Fig. 3. EEG power spectrum during task 8 – "imaginary rotation" with a biofeedback. At the end of the period the power for 10 Hz increases, because the user stops task's performance.

A comparative view of 10 Hz section is given on fig. 4. Introducing a feedback raises the quality of user's control.

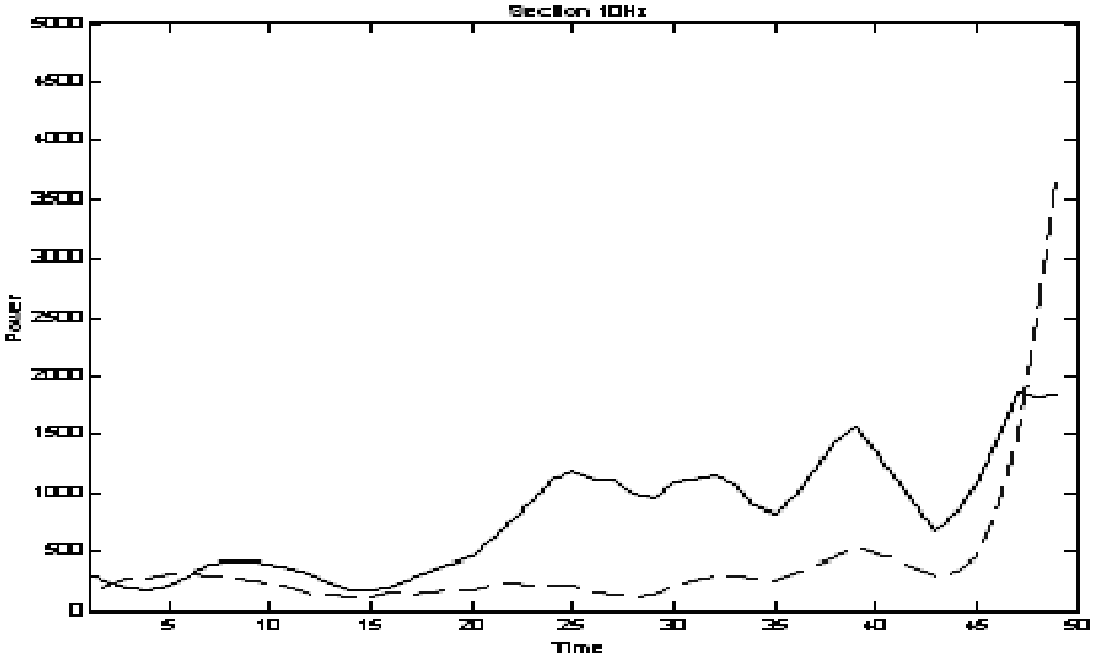

Fig. 4. Task 8, "Imaginary rotation" 10 Hz sections, without a feedback - solid line, with a feedback - dashed line

In connection to the discovered regularities the duration of mental tasks performance could be defined as: Without feedback information it is not recommended to perform tasks longer than 5 s. Longer time deconcentrates the subject and the quality of the EEG data is low. The effect is as well expressed for tasks that require completely relaxation and absence as for tasks that require a full concentration and mental effort. A learning effect along the different sessions was not noticed. For the baseline task the performance time is not necessary to exceed more than 2 s and it does not require a feedback. For other tasks: if the performance lasts longer than 6-8 s - the feedback is recommended.

The results from this study will be used to raise the quality of the EEG excerpts intended to form the input vector of a BCI's classificator from the existing database for final mental tasks' selection and during new EEG records.

REFERENCES

[1] Боянов, Б. Г., Цифрова обработка на сигнали, част 1, БРЯГПРИНТ, Варна, 2003, стр.162.

[2] Маноилов П., Преглед на ЕЕГ- базирани системи за комуникация, Трудове на научната сесия РУ'2005.

[3] Babiloni F., Cincotti F., Lazzarini L., Millan J., Mourino J., Varsta M., Heikkonen J., Bianchi L., Marciani M. G., Linear Classification of Low-Resolution EEG Patterns Produced by Imagined Hand Movements, IEEE Transactions On Rehabilitation Engineering, vol. 8, 2000, pp. 186–188.

[4] Curran E., Sykacek P., Stokes M., Roberts S. M., Penny W., Johnsrude I., Owen A. M., Cognitive Tasks for Driving a Brain-Computer Interfacing System: A Pilot Study, IEEE Transactions on Neural Systems and Rehabilitation Engineering, 12, vol. 1, March, 2003.

[5] Dumermuth G., Molinari L., Spectral Analysis of EEG Background Activity, In Gevins A. Remond A. (editors), Handbook of Electroencephalography and Clinical Neurophysiology, vol. 1, Methods of Analysis of Brain Electrical and Magnetic Signals, Elsevier, Amsterdam, 1987, pp. 85-130.

[6] Gysels E., Celka P., Phase Synchronization for the Recognition of Mental Tasks in a Brain–Computer Interface, IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 12, No. 4, December, 2004.

[7] Jenkins G. M., Watts D. D., Spectral Analysis and its Applications, Holden-Day, San Francisco, 1968

[8] Kamousi B., Liu Z., He B., Classification of Motor Imagery Tasks for Brain-Computer Interface Applications by Means of Two Equivalent Dipoles Analysis, IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 13, No. 2, June, 2005

[9] Malmivuo J., Plonsey R., Bioelectromagnetism - Principles and Applications of Bioelectric and Biomagnetic Fields, Oxford University Press, New York, 1995.

[10] Manoilov P.K., EEG Eye-Blinking Artefacts Power Spectrum Analysis, CompSysTech'06, V. Tarnovo, June 2006.

[11] Smith S. W., The Scientist and Engineer's Guide to Digital Signal Processing, California Technical Publishing, ISBN 0-9660176-3-3, 1997, http://www.castscope.com/dspguide.zip

[12] Townsend G., Graimann B., Pfurtscheller G., Member IEEE, Continuous EEG Classification during Motor Imagery—Simulation of an Asynchronous BCI, IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 12, No. 2, June, 2004

[13] Wolpaw J., McFarland D., Multichannel EEG-based Brain-Computer Communication, Electroencephalography and Clinical Neurophysiology, 1994, vol. 71, pp. 444–447.

[14] http://www.deymed.com/truscan32.asp

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