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BRAIN-COMPUTER INTERFACES

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CONTENTS

INTRODUCTION

The goal of new researches and technologies is to help and ease everyday tasks in life. Today, we can find the assistive technologies in everyday use, from the voice commands in smartphones to the eye tracking technologies. Those technologies emerged from the human-computer interface field of research. Brain-computer interfaces (BCIs) are part of this wide field of research. The main goal of such systems is to connect human (subjects) intention and the physical interaction with environment to do some task. In such a way, difficulties with interaction for people who are unable to use current devices (disabled persons) or are completely unable to communicate with outside world (patients with locked-in syndrome) are bypassed. The applications of the BCI systems can be of great help if they are developed for the people with severe neuromuscular damage, occurred as the effect of spinal cord injury, amyotrophic lateral sclerosis, stroke, or cerebral paralysis [1]. Besidea these specific applications, the BCI systems can be used as part of the biofeedback systems, to record our psychophysical state (perhaps even unaware of it) and use the computer to train us or adapt the environment to suit our needs.

The BCI systems include measurement, analysis and evaluation of complex neurophysiological patterns in the brain found in the electrical brain activity. BCI researches are involved in the multidisciplinary field of study due to a need for not only knowledge of the electrical sensors, amplifiers or signal processing, but also brain anatomy and cognitive and sensory process in the brain as well.

Each of the BCI systems consists of the measuring instrument for measurement of the electrical brain activity (EEG amplifier), computer host for processing of the recorded signals and feature detection characteristic for specific BCI system. The electric brain activity measurement can be invasive (electrocorticography) with the electrodes placed directly on the surface of the brain, and non-invasive (electroencephalography) with the electrodes placed on top of the scalp. Despite better signal to noise ratio and better overall quality of the signal, invasive methods aren't suitable for the everyday use or researches. Signal processing and classification are directly depended on the task instructed to the subject to do. Examples can vary, from the simple ones (input commands for computer and video games, manipulations in the smart house, wheelchair control) to complex ones like robot or artificial prosthesis control. On Fig. 1 general scheme of the BCI system is shown.

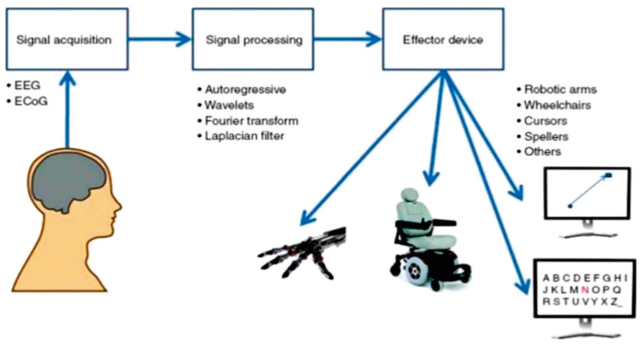

Fig 1. General scheme of brain-computer interface system (taken from [2] and modified)

BRAIN-COMPUTER INTERFACE BASED ON STEADY-STATE VISUAL EVOKED POTENTIALS

Steady-state visual evoked potentials

The steady-state visual evoked potentials (SSVEPs) belong to the visual evoked potentials group of brain activity. They are evoked as the brain reaction to current visual stimuli. Apart from the visual, there are auditory and somatosensory evoked potentials. SSVEPs occur with the flickering light stimulus. The amplitude is most expressed on the occipital brain region (visual cortex).

The characteristics of SSVEP are depended on the attributes of the stimuli (frequency and contrast). If the subject is presented with series of visual stimuli, which occur one after the other in uniform time intervals, the excited groups of the brain structures don't have time to return to the idle state. For stimuli, the black and white chessboard with alternating black and white fields is mostly used because of the strong contrast. As a result of such stimulus, high amplitude occurs in the frequency spectrum of the EEG signal from the occipital brain region, on the flickering frequency of stimuli. Scheme of BCI system with flickering chessboard as main stimuli is shown on Fig. 2.

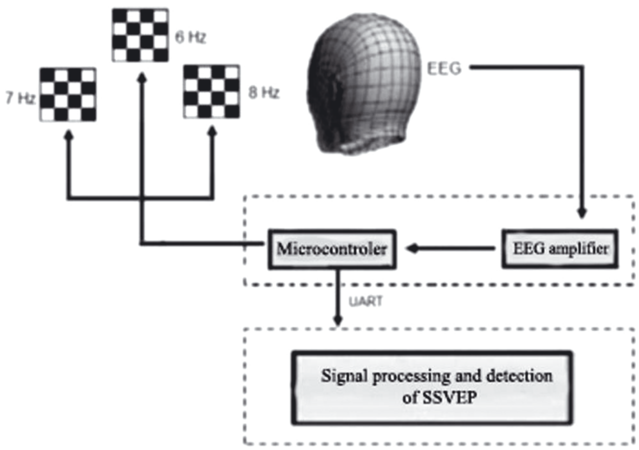

Fig 2. Scheme of BCI system with flickering chessboard

Detection and classification of eye gaze on chessboard

Brain-computer interface requires work in real time, so it is necessary to minimize the time of execution of the program code for feature extraction and classification of the eye gaze as much as possible. Given the short time of execution, Fourier transformation is selected as a method of analysis performed with Fast Fourier Transform (FFT) algorithm.

Before the Fourier transformation, over the previously filtered signal autocorrelation is carried out. The autocorrelation of the signal f (t) given by the formula:

$$R_{ff}(\tau) = \lim_{T\to\infty} \frac{1}{2T} \int_{-T}^{T} f(T) f(t-\tau)\, dt$$

Autocorrelation of the periodic signal is a periodic function of the same frequency as the signal, while autocorrelation of the aperiodic signal tends cancel out to zero for large movements [3]. Thereby, to decrease the influence of spontaneous brain activity in the EEG signal and to increase the influence of the periodic nature of the steady state evoked potential, autocorrelation is first used.

Classification of eye gaze on current chessboard can be performed by various methods such as machine learning and adaptive thresholding. In this case, a relatively rugged phenomenon is observed, so relative simple classification with thresholds at amplitudes of EEG spectrum at frequencies of chessboard oscillation and their harmonics is used.

Applications

Developed BCI can be applied in standard control and command applications, for example virtual keyboard. An interesting application is possible in smart homes, where such BCI, because of its robustness, can be used, for example in control of household lighting.

An important application of BCI system based on steady-state evoked potentials may be in video games for children with attention deficit disorder. Because of the need to subject to focus on stimulus, it is possible to design a game that would encourage concentration.

BRAIN-COMPUTER INTERFACE WITH ALPHA WAVE DETECTOR

Brain rhythms

Mental activities, emotional and psychological states, such as sleep, relaxation, solving of complex mathematical problems or discussions, are followed by different brain activity. Brain activity can be manifested in the form of brain rhythms (waves), called alpha (α), beta (β), delta (δ), theta (θ) and gamma (γ).

German neurologist Hans Berger first called perceived rhythmic EEG activity alpha waves. Alpha waves dominate in the occipital region of the brain and they appear in a state of relaxation. Their amplitude increases with eyes closed. The amplitude of alpha waves is not constant, but it changes in the shape of a spindle and then completely disappear and reappear after a few seconds. Alpha waves disappear during sleep and during enhanced cognitive activities (such as thinking, solving a problem). Alpha wave frequency range from 8 Hz to 12 Hz, while their amplitude is approximately equal to 50 μV.

Beta waves have lower amplitude than alpha waves and they occur mainly during increased brain activity (concentration, reflection, etc.). Also, they are dominant in patients experiencing anxiety. By opening the eyes alpha waves become blocked because the concentration of the patient increase and this causes the appearance of beta and disappearance of the alpha waves. Beta waves most commonly occur in the frontal and parietal region.

Theta waves and delta waves belong to the low frequency EEG spectra (<8 Hz) and have large amplitude relative to other waves. They occur in young children, or in a deep sleep in adults and may be an indication of abnormal brain disease.

Gamma waves are in the frequency range from 30 Hz to 100 Hz, and belong to the highest frequency range of the EEG waves. Until recently it was not seen as part of the EEG and they are only recently began to study more. Research shows that the brain enters the gamma state when high levels of processing information occurs.

In addition to the described dominant brain rhythms, mu rhythm has been recognised, also known as the Roland rhythm. It is located in the frequency and amplitude range of alpha rhythm, but topology and physiological character is different from the alpha. Mu rhythm is associated with imagining movement and motor movements. It is used for research of motor and sensory functions of the body, as well as in the rehabilitation of epileptic seizures.

The scientific community agrees that the alpha waves are an important source of knowledge and information on the functioning of the human brain and are often an inspiration to numerous studies of human behaviour, learning and concentration. Alpha waves get extra attention with the advent of biofeedback theory, which claims that it is possible to, at least partially, control the bodily processes that are normally controlled by the autonomic nervous system. Research of the alpha rhythm in conjunction with the biofeedback method presently shows interesting results in the treatment of depression, and phobias. In recent years, the alpha waves are increasingly associated with meditative states, while at the same time the positive correlation between high levels of alpha waves and creativity, better memory and faster problem solving is highlighted. Therefore, scientists are trying to find a method that would allow the conscious control of alpha waves [4].

Wavelet transform detection of alpha waves

The recorded EEG signal is first filtered with 4th order bandpass Butterworth filter with the limits f_1=3.5 Hz and f_2=40 Hz in order to avoid interference with the city power network noise. After pre-processing, signal feature extraction and detection of alpha rhythm by applying wavelet transformation is implemented. Wavelet mother function is the most important parameter in the analysis of the EEG signal because feature extraction signal depends on the correlation of the analysed signal and wavelet function. A group of orthogonal wavelet functions is chosen as one of the groups whose prototypes give the best results in the detection of alpha rhythm of the EEG signal. From the group of orthogonal functions wavelets Daubechies, Symlets and Coiflets are chosen and tested with Daubechies function of order 4 [5], Symlets of order 9 [6] and Coiflets the order of 5 [7].

By applying the discrete wavelet transform (DWT) details of eight levels are extracted. With sampling rate of 200 Hz, details of the fourth level (D4) includes the frequency band from 6.25 to 12.5 Hz. This frequency bands corresponds to that of alpha waves and the coefficients of these details are taken for further processing. On detail coefficient two methods of decision-making are applied to decide if the alpha waves are present. Both methods are based on the maximum absolute value of the wavelet transformation coefficients $M_j(T)$. Formulas for calculation of thresholds are given as:

$$Prag_1 = mean(M_j) + 2 \cdot std(M_j)$$

$$Prag_2 = 1.5 \cdot std(M_j)$$

where *mean*() i *std*()are functions of arithmetic mean and standard deviation, and M_j is defined as:

$$M_j(T) = \max\left|C_T(j)\right|$$

where C_T (*j*) is coefficient of level *j* given with wavelet transformations of EEG signal segment in given time T.

To test the method, the sections of 200 samples (1 second) of the signal are used. Slices were taken every 100 samples (half a second). If the 25% coefficient of wavelet transformation are larger than the set threshold, the presence of alpha waves is defined as positive. Otherwise, the presence is defined negative.

Based on the literature [8], we analysed the method of applying the Fourier transform to the previously calculated coefficients of wavelet transformation D4. The exact boundaries of the frequency band covered in detail depend on the prototype used wavelet functions, as well as the number of levels of decomposition. Therefore, the Fourier analysis can analyse in detail the content of component D4 and examine whether it contains, in addition to the alpha rhythm, any signals of other frequencies. With simple algorithm, only the value of the spectrum belonging frequencies 8-13 Hz are extracted and the power spectrum for an isolated area is calculated:

$$P(T) = \sum_{f=8}^{13}\left|X_T(f)\right|^2$$

The resulting power spectrum is normalized to the values between [0.1] in order to facilitate a decision on the threshold value. Threshold is set to be 0.25. If the total power of calculated standardized spectrum of segment is greater than 0.25 presence of alpha rhythm is defined positively, otherwise or negatively.

Applications

Biofeedback is a technique of treatment with which the patient learns to control the internal bodily processes which are normally automatically controlled by the autonomous nervous system (e.g. heart rate, blood pressure, muscle tension, body temperature, and EEG activity). By using EEG recording is possible to get feedback in real time on the concentration of alpha waves in the overall brain activity, which is an indication of the current calmness and relaxation. Currently the most popular application of biofeedback techniques if for meditation, because it has been observed a significant increase in the concentration of alpha waves during deep meditative state. Biofeedback techniques has found its application in the treatment of phobias, depression, and calming hyperactive children and in practice with children with speech difficulties. Psychologists also found the application of alpha waves in the training of soldiers, to train their ability to increase the concentration of alpha waves successfully if they undergo lie detector. Probably the most interesting application of biofeedback techniques today is in business environment of high risk. In fact, studies have shown that the concentration of alpha waves increases by as much as 25% before the respondent makes a mistake, then again observed a significant decrease in their concentration when the subject becomes aware of such errors. This correlation is important in high-risk occupations (e.g., air traffic controllers). By using biofeedback methods, we can alert in time when their concentration falls or when they start automated and unknowingly perform a task [9]. In addition to these, biofeedback application will find benefit in many other aspects of life and business, especially when it comes to still unexplored characteristics and effects of alpha waves. Therefore, reliable and fast extraction of alpha rhythm of the entire EEG signal is of great importance.

BRAIN-COMPUTER INTERFACE BASED ON MOTOR IMAGERY

Brain activity during motor imagery

Two types of brain activity occur during the execution of movement (a similar activity occurs during the motor imagery [10]): movement related cortical potentials (MRCPs) and changes in the amplitude of sensorimotor rhythms (SMRs).

The primary somatosensory cortex is in the anterior part of the parietal lobe, while the primary motor cortex is located at the posterior part of the frontal lobe, separated by large fissure called central sulcus. Fig. 3 shows the division of the brain into the lobes and parts responsible

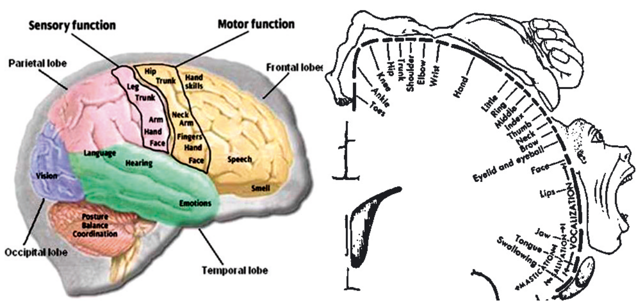

Fig 3. Functionality of different parts of the brain (left) and homunculus of motor (right) (taken [11])

for sensory and motor functions.

A more detailed breakdown of motor cortex is shown on the left side of Fig. 3, and it is called the homunculus (Latin for "little man"). Fig. 3 shows that some part of the body has a different surface area of regions responsible for its control. Both feet have relatively small representation in the primary motor cortex, while the hands have relatively large. The reason for this lies in the complexity of the movement that we can perform with your fingers, unlike those with those. The importance of this in the context of the brain-computer interface is in choosing the parts of the body with which we control the BCI. Only the part of the body with enough large representation on the motor cortex provide useful control signals. In addition, the activity of the hand is

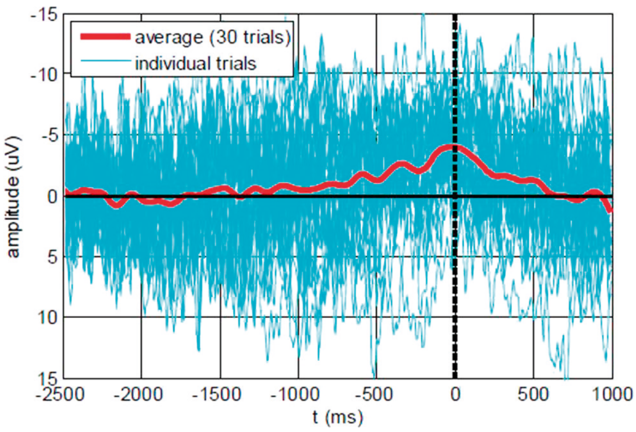

Fig 4. Averaged MRCP (red) i individual trials of EEG signal (blue) (taken from [11])

read on the contralateral hemisphere of the brain (left arm activity occurs in the right hemisphere, and vice versa). That way it is easily to distinguish which participates in the control, while the differentiation of the activity of the left and right foot is a difficult task.

In these regions, MRCP emerge during the planning, preparation and execution of movement. For causing visible activity of MRCP recorded with EEG, it is necessary to repeat the same movement several times after which the recorded brain activity is averaged (Fig 4.). Small amplitudes (a few microvolts) in relation to the spontaneous brain activity, together with a large variability in time relative to the movement, makes MRCP unsuitable for use as control signals in the BCI systems since it takes time for extraction of recognisable waveform.

Somatosensory rhythms show two types of amplitude modulation when performing movements: evoked desynchronization (ERD) and evoked synchronization (ERS). Within the frequency band of a mu rhythm, evoked desynchronization occurs as amplitude attenuation during the preparation and execution of movement, while evoked synchronization occurs in the beta frequency band as an amplitude gain, after the movement. Unlike traditional evoked potentials (obtained by averaging), which can be observed as the major series of postsynaptic responses of pyramidal neurons activated to some stimuli, ERD / ERS can be observed as a change in one or more parameters which control the oscillations of the neural structures. These changes are not phase related to the event, so time-frequency analysis is needed.

Time-frequency analysis of evoked desynchronisation and synchronisation

To extract features characteristic for the evoked synchronisation or desynchronisation, it is necessary to carry out time-frequency (TF) analysis. Often the simple bandpass filtering of bandwidth of interest is used. By comparing the power spectrum with baseline levels averaged prior to the execution of movement it is possible to extra-

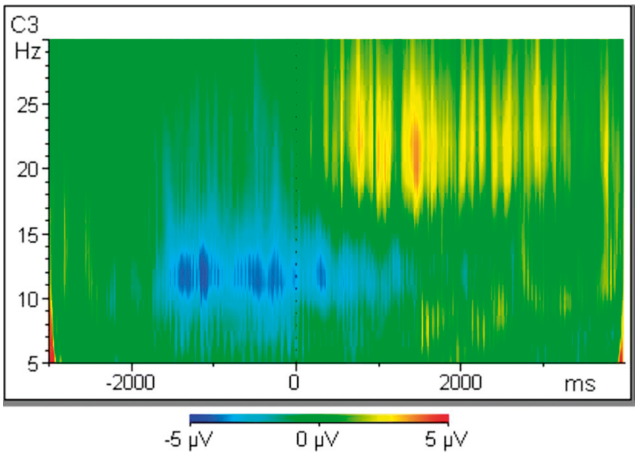

Fig 5: Evoked desynchronisation and synchronisation during right hand movement (recorded on C3 electrode)

ct the appearance of desynchronisation or synchronisation (Fig. 5).

It is shown that by using more complex mathematical methods, such as Hilbert-Huang transformation, can improve the quality of classification. Hilbert-Huang transformation for real signals is given by:

$$h_H(t) = H\left[x(t)\right] = \frac{1}{\pi} PV \int_{-\infty}^{\infty} \frac{x(\tau)}{t-\tau} d\tau$$

Because of the large signal individuality of each subject, greater accuracy is achieved by selecting individual time and frequency window in relation to the moment of the beginning of movement imaging. In Fig. 6, the different classification accuracy for different time windows and frequency bands is shown.

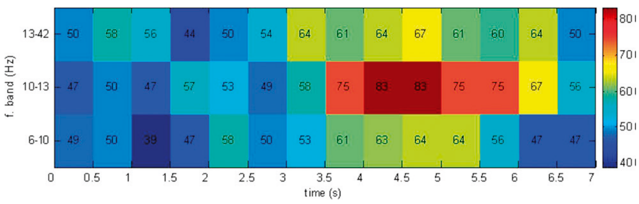

Fig 6: Classification accuracy for different time-frequency bins(taken from [11])

Applications

The use of this BCI system feels the most natural in the control applications, where imagining particular movement commands (e.g., imagining the movement of left hand moves a wheelchair to the left). An interesting application of movement imagery is in the rehabilitation of patients of a stroke. Imagining movement provides one mode to rehabilitation during training movement [12]. By applying the BCI system it is possible to give feedback to the patient in rehab, which would speed up his recovery.

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