Design Adaptable BCI Based on Evoked Potentials

Martin Hošna[1]

***Abstract*— In this article we deal with posibilities of adaptation in brain computer interface (BCI) systems. Main attention is given to systems based on electroencephalography (EEG). We also introduce posibilities of adaptation and improvement of performance during fatigue through combination of steady state visual evoked responses (SSVER) and event related potential P3.**

I. INTRODUCTION

The race for performance became a big hit in last years in the field of BCI. Parameters generaly used to quantify the performance of BCI systems are the accuracy and speed (bit rate). One of often left out things at the experiments with the duration of tens of minutes is fatigue and comfort of the subject. The fatigue may cause a performance drop and also raise the number of false choices.

The goal of the Brain Computer Interface is to create communication channel between the brain and the computer.

A. Basic structure BCI

The common structure of a Brain Computer Interface is the following [1] (figure 1):

- Acquisition (invasive or non-invasive method) and amplification
- Pre-processing (e.g. noise and artifacts removal)
- Classification (find out which kind of mental task the subject is performing)
- Computer interaction (may be very various - depends on specific application). For example system can move with cursor or turn on/off the light.
- Feedback

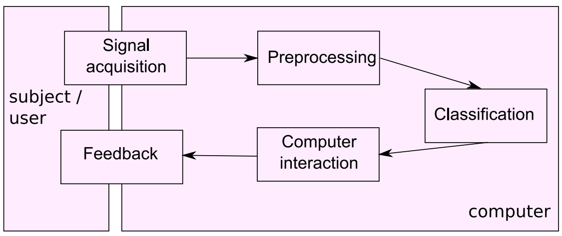

Fig. 1. Scheme of BCI

B. Operating modes

BCI operation mode can be synchronous or asynchronous. In synchronous BCIs, the system is active only during some time periods. The period is defined by the system or can be chose by subject. The BCI system also processes the signal only in specific time according to the period. The advantage for development is that the onset of the mental activity is known a priori and usually associated with stimulus. Asynchronous BCIs are always active and react only when the subject performs the control. An ideal asynchronous BCI system uses no cue stimulus and the subject is free to intend whatever he/she wants ([2], [3]).

C. Feedback

Learning to operate a BCI is similar to learning tasks like walking or speaking, involves many of the same learning mechanisms and also requires training and practice. The presence of feedback is the most important element of such learning. During the learning process the subject makes adjustments based on feedback in order to improve their skills appropriately. However some types of BCI are based on natural brain response and they don't need to involve learning.

The feedback may be continuous or discrete. Continuous feedback is provided immediately and smoothly usually by a visual cue (e.g. movement of mouse cursor). Discrete feedback involves typically two value indication of success.

The quality of provided feedback can affect the speed of user training. Unfortunately which type of feedback is the best appears to be a subject dependent issue.

II. NEUROPHYSIOLOGICAL BACKGROUND

In this article we give a short description of related neurophysiological background of BCI system. More details and another paradigms are in [4].

A. Evoked potentials

Evoked potentials are brain potentials that are evoked by the presence of a sensory stimulus. Evoked potentials can provide discrete control when the BCI system produces the appropriate stimuli. This paradigm requre little or no training to use the BCI with the disadvantage that the user has to wait for the relevant stimulus presentation.

1) P3: The evoked potential P3 is a positive wave in the EEG signal peaking at around 300 milliseconds after task-relevant event. P3 is component of evoked potentials and its general form is shown in figure 2. Potential P3 can be evoked by many types of paradigms. Most common influencing factors are the frequency of stimulus occurrence (less frequent stimuli produce a larger response) and task relevance. Cognitive potential P3 enable discrete control in response to auditory or visual stimuli.

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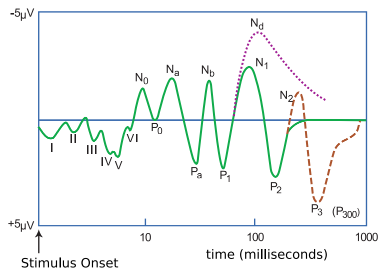

Fig. 2. Idealized waveform of P300. The solid line is waveform without P300. Dashed line illustrates occurrence of P300. [5]

2) Steady State Visual Evoked Responses: SSVERs are caused by a visual or auditory stimulus that is modulated at a fixed frequency. Repeated occurrence of the stimulus leads to an increase in the EEG activity at the same frequency and at harmonics and subharmonics of the stimulation frequency.

An SSVER can be detected by examining the spectral content of the signals from electrodes O1 and O2 of the 10-20 international system (see figure 3).

Several actions can be associated with targets flickering at different frequencies. The subject can then control the BCI by looking at the target corresponding to the desired action.

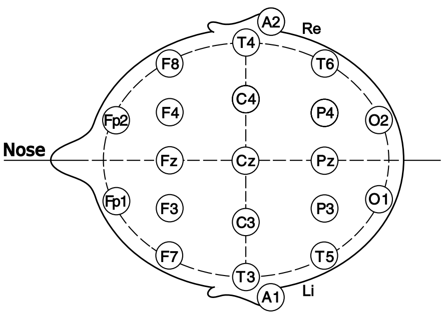

Fig. 3. International 10-20 system of electrode placement

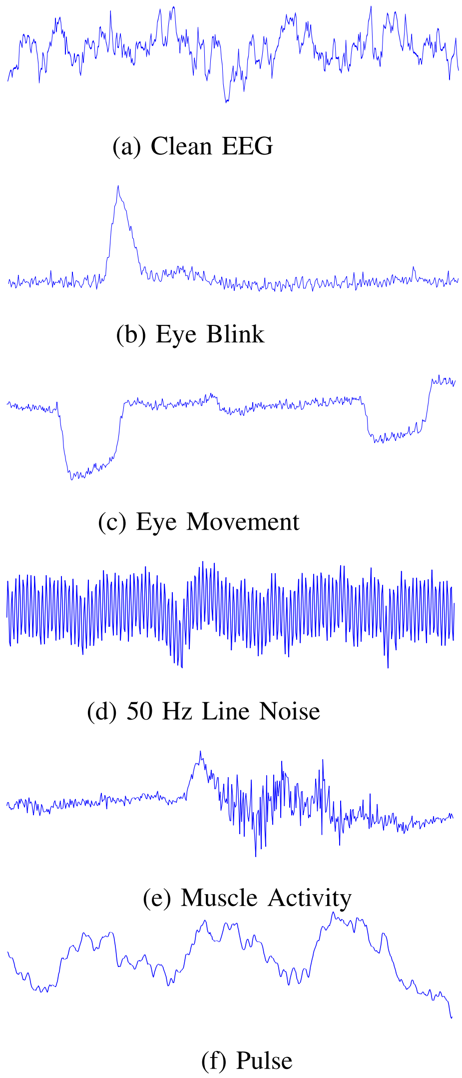

Fig. 4. Artifact waveforms [7]

III. PREPROCESSING

A. Artifacts

One of the significant problem while automatic processing EEG signal is the presence of artifacts. Artifacts are signals contained in the EEG which are of non-cerebral origin. Some artifacts may modify shape of a neurological phenomenon that drives a BCI system ([6]). In figure 4 there are differend kinds of artifacts displayed which typically occur in EEG signal.

1) Avoid artifacts: First method of handling with artifacts is to avoid their occurrence by issuing proper instructions to users (e.g. users are instructed to avoid blinking and muscle activity). The main disadvantages of this method are:

- Some artifacts will always be present in the brain signal e.g. the heart beats.
- While online processing it is not possible to totally avoid blinking or muscle activity.
- Collecting a sufficient amount of data can be very difficult.
- Artifacts avoiding can cause another cognitive process in the brain.

2) Artifacts rejection: Artifact rejection consists in rejecting the trials affected by artifacts. Rejection is done by visually inspecting the EEG or by using an automatic detection method. Main disadvantage of manual rejection is the cost of human labor. Main disadvantage of artifacts rejection is inability of reaction of BCI in the time of rejected trial.

3) Artifacts removal: Artifact removal is the process of identifying and removing artifacts from brain signals. There are several methods for artifacts removal (you can see more in [7]).

4) Applied method: Considering that this work is aimed on dealing with fatigue and extension time which is is user able to control BCI, we use automatics artifacts removal method. This method is the combination of a frequency filter and rejecting time trials with strong artifacts.

IV. ADAPTATION

There are three basic types of adaptation in BCI systems (figure 5, [8]). The first one is operant conditioning paradigm and is based on user adaptation tn the BCI system. Operant conditioning often requires a lot of time before good control of BCI is achieved. The second one falls into category learning machines and the BCI system to be mainly a problem of machine learning. Third type considers the user and also the BCI system as the interaction of the two dynamic objects . This involves selection of signal features that the user can control best and optimization of recognition signals provided by the subjects brain.

Adaption in BCI systems, where data is not stationary, is useful to improve the performance. In ideal case the adaption is not only stable bud also fast. Adaption can be done:

- globally or in intervals,
- once or repeatly,
- at the start of a session or continuously,
- user dependent or independent.

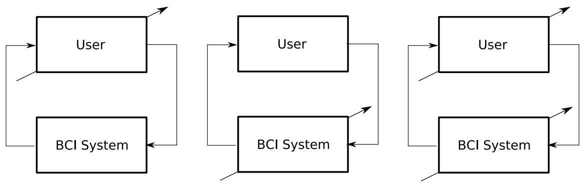

Fig. 5. Three basic types of adaptation in BCI systems. In the first case only user is adapted (e.g. operant conditioning). In the second the system is adapted on the user or situation. In the last case it is a combination of the previous.

Adaptation of the user (see figure 5) is out of scope of this paper.

Let's look more closely at the adaptation of the BCI system. The scheme of the BCI system is in Figure 1. In principle each part of the BCI system may be adapted. The BCI system adaptable parts are:

- Signal acquisition: for each subject the most suitable type of signal acquisition can be selected. It can be done e.g. according to user comfort, user possibilities, environment or usage.
- Preprocessing: during the signal preprocessing changes of the conditions should be taken into account. During the use of the BCI system it is not possible to avoid all surrounding influences. We can't rely on the facts that the measurement takes place in an isolated room and that there is no muscle activity. The preprocessing should react to the situation. One of the possible reactions can be the change of freature extraction or used cortical process (if possible).
- Feature extraction: on this place we can change cortical process used for control the BCI (can depend on signal preprocessing). One cortical process can be in specific situation or for specific subject better than the another. Another more complicated option is to have simultaneously more ways to get the features.
- Classification: we can have classifier
  - for each subject or for all;
  - once learned, at the start of control or continuously learning;
  - different classifier for specific situations;
  - using specific features in specific situations.
- Computer interaction: here we have very big field of possibilities but it is very dependent on the concrete BCI system. For example in the case of occurrence of a lot of errors, the system can include confirmation of each decision or the time reserved for one decision can be prolonged.
- Feedback: it is also very dependent on the concrete BCI system. For example in the case when great noise is detected the volume of auditory feedback can be increased or can be supplemented by visual feedback etc.

As you can see, in the BCI system there are several posibilities and places for adaptation. We can use only one place or posibility for adaption or we can adapt more than one at once. When we decide to use more places then it's good to have some adaptation logic. Adaptation logic is part of the BCI system that coordinate adaptation in whole system. For example we can watch bit rate, accuracy, amount of noise, number of artifacts or false positives. Some characteristics are easy to watch (like amount of noise or nuber of artifacts) and for the others we need some additional resources (like false positives or accurancy) for determination. When we have the adaptation logic then we can adapt some or more parts if necessary. The adaptation logic also has to include rules how to react at different situations. For simplification of the logic, we can use more, not exclusive, ways to get the decision from the subject. One example can be use of movement related potentials and event-related desynchronization (see [9]). This procedure, in a little different way, is introduced in the next section (combination of SSVER and event related potential P3).

Adaptation in BCI system can be found in several works. For example:

- Approach of Fabrizo Beverina in [10] is making the computer adapt to the human brain activity. is making the computer adapt to the human brain activity.
- M. Kawanabe presents [11] the adaptive classifier for BCI based on a mixture of Gaussian (moG) model of the features and a dynamical Bayesian model of the class means.
- Johan Philips presents in [12] this adaptive shared control system for the BCI controlled wheelchair.
- Anna Buttfield in [13] deals with methods of adapting the classifier while it is being used by the subject.

V. DESIGNED PROCEDURE

As mentioned above the fatigue may cause a performance drop and also raise the number of false choices. The goal of the designed experiment is the improvement of performance during fatigue. For this purpose we proposed three variants of combination of SSVER and evoked potential P3.

Common for all variants: The subject is sitting approx. 50 centimeters away from a computer screen (CRT monitor with 85 Hz refresh rate). On the screen there are four options presented. Each option is represented by a simple picture and a short description of the option. Options are sorted by prior probability.

The users are asked to chosen one option and gaze on the picture representing the choosed option.

Variants description:

1. All pictures representing the options (see figure 6) are flickering at different frequencies. The frequencies are chosen accordingly to avoid harmonics interaction. The detection of the increase of EEG activity is done through analysis of the channel O1 and O2 (10-20 system, see figure 3). At a positive finding of on increase in activity the specific option is in addition highlighted or color is changed or color space are changed from gray to color (depends on scenario). After that evoked potential P3 is detected. An option is chosen when the minimum-probability threshold is reached. Total propability is given by sum SSVEP and P3 propability.

Fig. 6. Example of four options represented by pictures.

2. This variant is only small modification of the first one. The aim of the modification is to improve user comfort at controlling the BCI. Flickering pictures can be very uncomfortable and annoying. In this variant only the borders of the pictures flickering.

3. The single trial analysis of P3 component is primarily used for the detection of the decision. Each option is highlighted in sequence and evoked potentials are detected. An option is chosen immediately when the immediate-probability threshold is reached. If no option is chosen in that way the option with the maximal achieved probability is selected. However the maximal probability still has to be bigger than the choice-probability (constant determined empirically). When no option was chosen then the steady-state visual evoked potential is used. Each highlighted option is also flashing at different frequency. Probability of every option is determined by combination of the detection of EEG signal modulation to flashing frequency and the detection of evoked potentials.

VI. CONCLUSION AND FUTURE WORK

This work does not contain new methods or new settings of methods for EEG signal processing. This article is about how can the current methods used to achieve determined goals. We presented three different procedures for combination of two paradigms as a solution to our goal. Unfortunately we can not at this time support these procedures with the results of experiments because of troubles with online communication with our EEG device.

In future work we intend to test and compare different ways of adaptation of BCI systems. Main attention will be given to ways which are not commonly used to adapt BCI system.

VII. ACKNOWLEDGMENTS

This work was supported by project ME 949 Analysis of negative impacts on driver attention and 1F84B/042/520 Methods and tools for detection and prevention of driver attention decreases

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