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Research Paper

A Novel Method in Attention Measurement for Operators of Radar Devices Based on P300 Event-Related Potential Protocols Detection

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Abstract: Various methods have been proposed to detect the attention and perception of an operator during tasks such as radar monitoring. Due to the high accuracy of electroencephalographic signals, it is utilized for systems based on brain signal. The event-related potential (ERP) technique has been widely used for testing theories of perception and attention. Brain-computer Interface (BCI) provides the communication link between the human's brain and an external device. In this article, we propose a method to investigate the attention of operators of very sensitive monitoring devices, in particular, the operators of navy ships' radars in detecting fighter aircrafts. Using a Visual Stimuli, which was shown to the subjects prior to the test, the protocol utilized in this paper yielded a very high accuracy (up to 87%), which makes it a robust method to use in such conditions. Linear LDA and non-linear SVM classifiers were utilized in processing the output signal. Although several P300 systems have been used to detect attention using pattern recognition techniques, the novelty of this study is that attention detection is used for the first time for a radar operator which resulted in acceptable accuracy.

Keywords: P300, Event-Related Potential, Radar, Visual Stimuli, Attention.

1 Introduction

BCI systems have a variety of capabilities and applications. These systems are used for both healthy people and people suffering from severe mobility disability [1]. Applications of BCI systems include robot control [2], speller [3], gaming systems [4], and etc. In fact, BCI systems have the ability to create a direct path for the human brain to connect to a computer. According to the above description, two main functions are defined for BCI systems: 1) A BCI system must be able to detect neural activity in the brain and identify the user's target, and 2) This system must translate and interpret brain signals into executable commands for an external device [5].

In 1924 German psychiatric Hans Berger recorded the first electric field of the human brain. The recorded signal was named electroencephalograms (EEGs) [6]. In recent years, this signal has drawn great interest in the investigation of cognitive processes in research and clinical areas [7, 8].

The advantages of this method are non-invasive measurement, low cost, ease of implementation, and superior temporal resolution [9]. The brain-computer interface (BCI) is a communication method that transforms the neural activities of the human brain into commands understandable for an electronic device [3]. According to reference [10], BCI systems can be divided into two general categories: 1) Independent-stimulus systems and 2) Dependent stimulus. In Dependent-stimulus systems, an external stimulus is used to excite a component in the subject's brain waves and this component is extracted using computational methods and pattern recognition techniques. But in independent-stimulus systems, brain activity is independent of external stimuli [10]. One of the common BCI systems based on Dependent-stimulus is

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event-related potential (ERP)-based systems. The two most prominent components used in ERP-based systems are P300 and SSVEP. The P300 component is a positive potential that appears with a delay of about 300-500 milliseconds after the onset of stimulation. The P300 component is evoked in an oddball paradigm when a target stimulus appears in the midst of a series of non-target stimuli. This component is more clearly observed in the central electrodes (Cz, Pz, Fz) rather than in other electrodes [11, 12]. SSVEPs are potentials that appear in response to a visual stimulus, mainly at the electrodes and the occipital lobes of the parietal brain. This component is triggered when the user looks at a flickering stimulus at a constant frequency [13, 14].

In the past few years, many potential applications of the event-related potential-based P300 component have been studied [15, 16]. The ERP is measured by averaging the EEG signal time-locked to a specific event (visual or auditory stimuli). The components found in these tasks have waveforms with identifiable characteristics that are named after their latency and polarity (i.e. P300, P200, P100, N200, N100). P300 is a peak in the EEG approximately 300 milliseconds after applying a certain type of stimuli (task-related). The amplitude is the difference of voltage between the established base prior to the stimuli and the largest positive peak within a certain latency window [17, 18].

Rapid serial visual presentation (RSVP) is a typical example of BCI systems. RSVP is used particularly in target image detection. In this method, a series of images are presented sequentially and rapidly to a subject on the screen. As soon as the participants see the target image, there is a very high chance that P300 would occur [19]. The P300 signal, in this case, would appear as a peak in the EEG approximately 300-500ms after the target image was presented [20].

The key question to ask may be whether one's attention affects information processing at the sensory stage or later. There are obviously cases where attention happens after receiving a stimulus. For example, a subject may see the stimulus and simply decide not to give it a clear response. It is much more difficult to determine whether attention can possibly suppress the sensory processing of a stimulus. In fact, it is not certain that traditional behavioral practices have yet obtained unambiguous evidence. However, ERPs are very useful for addressing the attention detection of a subject.

In order to investigate this phenomenon, we compare the ERP waveform generated when the subject is paying attention to the stimulus to the ERP waveform generated when the subject ignores the stimulus. The earliest point in time at which the two signals differ provides an upper bound on the initial effect of attention on the processing of the stimulus [21].

In order to detect the attention of the subject in the traditional face-to-face structure, the gaze and facial expressions are used. Nowadays, many studies have been carried out to detect and measure attention using brain signals [22]. Various processing methods were introduced for checking the user's attention. One method is to determine the amount of attention by assessing changes in frequency bands in different areas of the brain [23]. Another method is feature extraction and application of pattern recognition methods [24, 25]. In addition, it should be noted that the study of user attention was carried out for both healthy and sick subjects (especially children suffering from ADHD) [26].

In this paper, we take advantage of ERP waveform and cognitive capabilities of such potential to propose a repeatable test in order to examine the attention and focus of operators of sensitive monitoring devices such as radars in a navy ship. In order to achieve this goal, the participants were asked to focus on the radar monitor and expect sudden images to appear which contain aircrafts on them since the participants were familiar with the image of an aircraft this information grants the cognitive requirement of this procedure (Different sections of the paper are demonstrated by a block diagram in Fig. 1).

2 Material and Methods

2.1 Subjects and Experimental Protocol

A total of two male users aged between 26 and 30 participated in this experiment. Each participant is used for the stimulation protocol in one test session. All users were chosen from students and had no previous training in this experiment. Before each experiment, users took medical tests to ensure mental and physical health and fitness. Test protocols have been reviewed and approved by the Ethics Committee of the Iranian Medical University. All users have volunteered to participate in this experiment.

2.2 EEG Signal Acquisition

EEG signals were recorded using an 80-channel g.HIamp (G.Tec company) system. Electrodes were placed according to the International 10-20 System. EEG was recorded on 32 channels. One earlobe was served as the reference. The sampling frequency of the signal was 512 Hz and a digital notch filter was applied at a frequency of 50 Hz.

2.3 Experiment Design and Procedure

In this study, the stimulus protocol has been designed and tested to detect whether the user is paying attention or not. In this protocol, triggers are displayed in the gray background. Before displaying the triggers for previewing as shown in Fig. 2, first "'PAY ATTENTION TO SCREEN'" is placed at the top of the screen for 2 seconds, then the fixation cross is displayed for one second which indicates the start of the experiment and eventually triggers will be displayed sequentially.

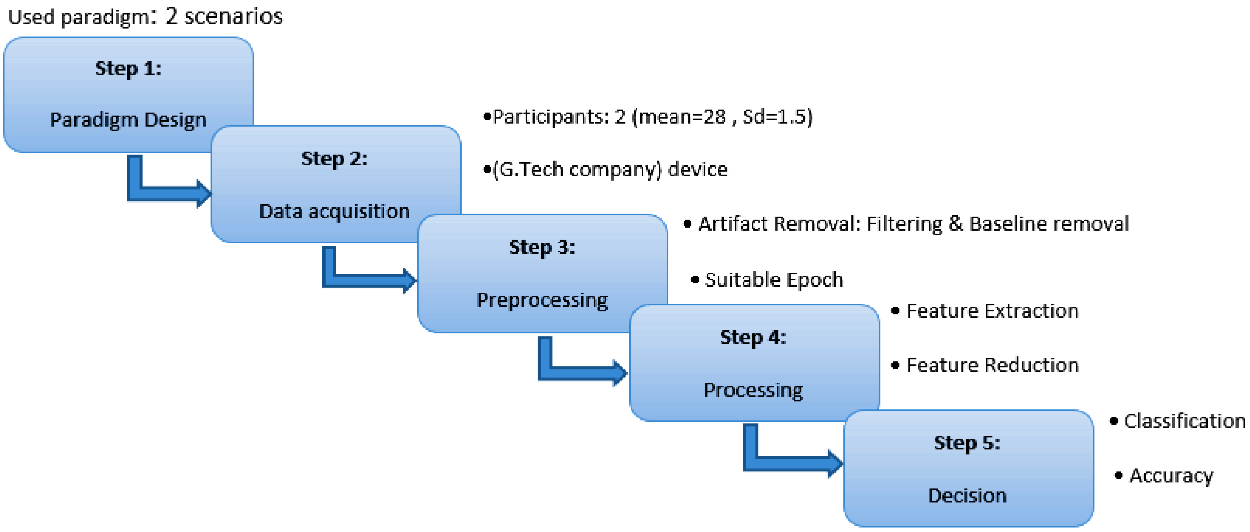

Fig. 1 Demonstration of main steps of the proposed method, including paradigm design, preprocessing, and main processing of EEG signals.

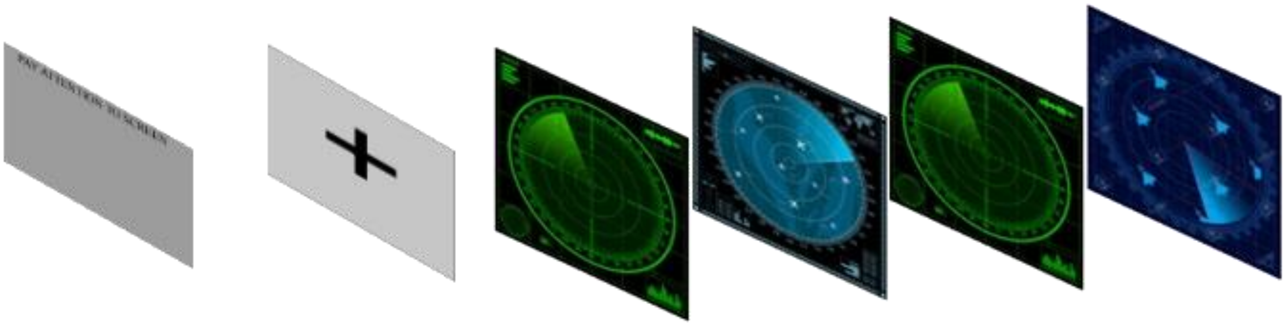

Fig. 2 Stimuli presentation structure.

In each run, the provocations are repeated 5 times, and each fighter's avatar is displayed four times each time. Thus, in each run, 20 images are displayed, which include a fighter aircraft.

Users were sat about 100 cm from the screen on a comfortable chair. Each user was tested with the above-mentioned three excitation protocols. During testing, this protocol is tested in offline mode in two different scenarios. In the first scenario, the users were instructed to identify the fighter's image. During the test, the users have also been instructed to count the number of times that the target is observed. In the second scenario, the user is asked to not focus on stimuli and focus as far as possible on the corner of the monitor in order to not see the image of the fighter. According to [10], the subject's response to stimulation is divided into overtly and covertly. In the present study, the subject's response to stimulation is received overtly and also only the brain's electrical activity and EEG signal are used to assess the user's response. The user does not use any muscular force or external feedbacks such as pressing the key to responding. The user is only asked to count the number of target images which is done to increase the user's attention and focus in the experiment. Testing this protocol is done in several runs and in one session. Each run contains 15 images of the target. Between each run, the user rests for a few minutes.

2.4 Data Analysis

First, for ERP analysis, all channels were filtered by a passive filter in the range of [0.2-30] Hz and then were down-sampled at a 512Hz frequency. In the following, EEG signals were divided into Epochs ranging from 0 to 1000 milliseconds after initiation of stimulation. Baseline correction in each Epoch is used from 100 to 0 milliseconds before each stimulation. To remove artifacts such as blinking, since the recorded EEG signal range is between -50 and 50 μV, epochs with a difference of 120μV range between the maximum and minimum amplitude are considered artifacts and the entire epoch is removed from the signal.

To extract the properties, both time and frequency features are used. Temporal samples are used as time attributes. Among different frequency characteristics presented, the wavelet transform is an efficient feature for distinguishing between non-target and target stimuli in ERP analysis [27-29].

To calculate the wavelet transform coefficients, like Fig. 4 on each epoch, a five-octave discrete wavelet transform was applied to the original wavelet "bior 2.2" [29]. Fig. 4 shows the obtained wavelet coefficients for target and non-target stimuli (the blue

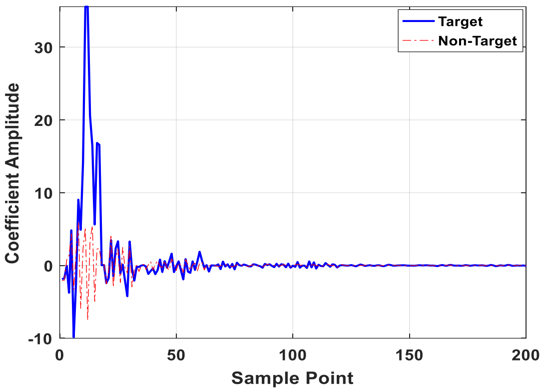

Fig. 3 Frequency coefficients of wavelet transform were obtained from the 5-step discrete wavelet transformation.

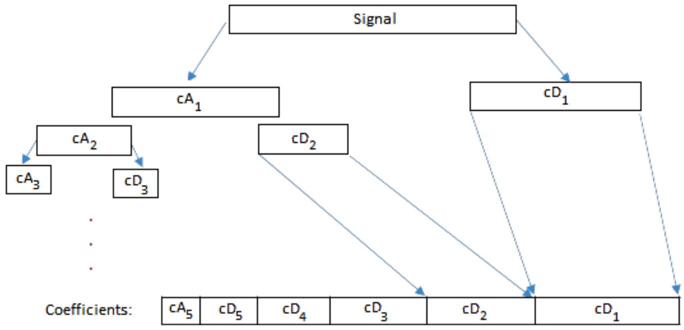

Fig. 4 Five-stage wavelet decomposition. At the first step, the signal is decomposed to coarse Detail (cD1) and coarse Approximation (cA1) and it keep on.

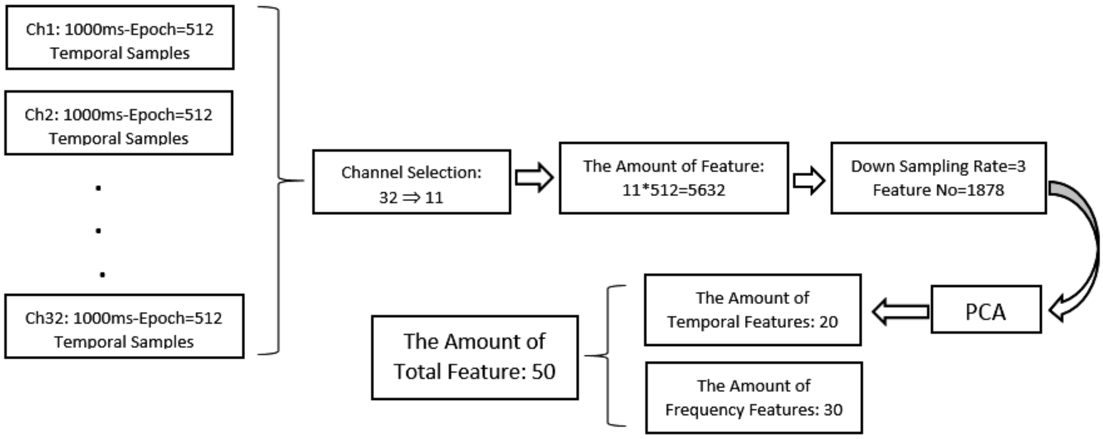

Fig. 5 Detailed demonstration of the amount of different features. Two kinds of features including temporal and frequency features are used.

and red charts show the wavelet coefficients of the target and non-target stimuli, respectively).

As shown in Fig. 3, most of the signals in the wavelet domain are limited to an initial number of samples, and the same samples determine the most distinction between the non-target and target signal. Therefore, only the initial wavelet coefficients (the first 30 samples) are used. Then the time samples and the wavelet transform coefficients are put together.

From the 32 available channels F3, Fz, F4, Fc1, Fc2, Cz, Cp1, Cp2, P3, Pz, and P4 are used in our experiments. These channels have been selected for two reasons. 1) In most papers, most of these channels have been used to detect P300 [30-32], 2) These channels show more robustness on our data than other channels for detecting P300.

According to Fig. 5, at first, we separate 1000ms-windows as epochs and then all epochs are downsampled with the frequency of 512 Hz. So we would have 512 temporal samples. We had 32 channels but we only used 11 channels. In fact, we performed a spatial filtering (channel selection or feature reduction in spatial domain). Regarding 512 temporal samples, the amount of features is equal to 5632. After downsampling with the rate of 3, we had 1878 temporal samples. For feature extraction by PCA, we extracted features that maintain 99% energy of signal (covariance matrix). Finally, we obtain 20 temporal features. In addition, wavelet transform coefficients were obtained using a 5-step discrete wavelet transform. By applying this wavelet transform, the signal is decomposed into coarse approximation and coarse detail. Wavelet coefficients can be obtained by placing approximation coefficients from the last stage and detail coefficients from different stages together.

For object classification and character recognition, two classifiers were used: one linear classification LDA [33] and one nonlinear SVM [31], and the results of these two categories are compared.

2.5 Performance Evaluation of the Algorithm

The performance of classification algorithms and stimulation protocols are evaluated by the objective accuracy criterion. In this test, the accuracy of the classification is calculated in two cases. 1) Detecting the target occurrence when the user's attention is directed to non-target stimuli. 2) Detecting the target occurrence when the user is not paying attention. To determine the accuracy of the classification algorithms used, five-fold cross-validation was performed.

3 Results

3.1 ERP Analysis

In Fig. 6, the Grand-average of the P300 component for a subject and for electrode Pz is shown. In the blue line (or red), the ERP response to target stimuli and the red charts shows the response to non-target stimuli. In all diagrams, the main component is clearly seen, the P300 component is created with a delay of about 300ms after initiation of stimulation in the central region of the lumbar region, which is shown in Fig.7.

The topography of the skull at different times of the test also indicates the extent to which brain activators in which region and with what latency from the onset of stimulation will be maximized. In brain topography, the difference in brain activity is clearly visible in non-target and target stimuli. In these topographies, no activity is observed in the non-target stimuli. On the other hand, for the target stimuli at a time of about 400-500ms, the activity of the brain is maximum, and this activity is located in the center of the skull, where the cognitive cortex is located, and it is confirmed that there is a P300 occurrence in the area.

3.2 Classification

For offline classification, one non-linear SVM and one linear LDA are used. The accuracy of the character recognition obtained from these two classes is reported for different states and different users in Table 1. For training the SVM classification using non-linear SVM with Gaussian kernel, stratified parameters (c, σ) are set to optimal values using trial and error.

In mode 1, the user was asked to completely focus on the screen and wait for the trigger image to appear, on the other hand in mode 2 the user was asked to deliberately avoid looking at the screen. In this study, the results for offline categorization, the mean detection accuracy obtained for mode1 and mode2 are 75.68% and 84.4%, respectively.

In fact, the results of the second case are not just the data of the second scenario. Rather, the target stimulus data in the first scenario (which the user paid close attention to and counted to evoke a stronger P300 component) were categorized with the target stimulus

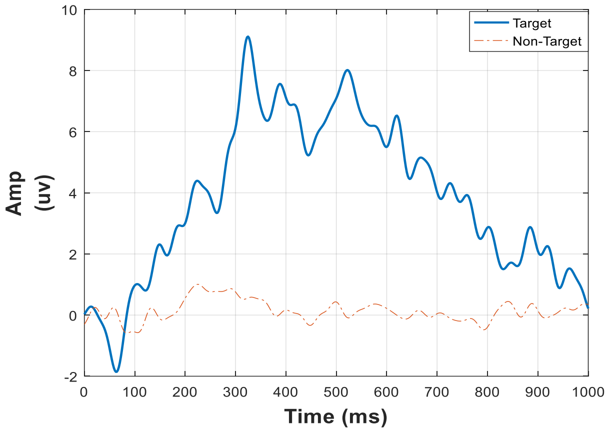

Fig. 6 Target and non-target ERP component curves for an individual subject. In each plot, the blue curve corresponds to the target and the red curve corresponds to the non-target P300 component detection.

Table 1 Target detection accuracy using LDA and SVM classifiers in two different modes [%].

Classifier	SVM		LDA	
Mode	Mode 1	Mode 2	Mode 1	Mode 2
Subject 1	71.3	72.8	73.3	87.5
Subject 2	78.3	71.9	78.0	81.3
Mean	74.8	72.35	75.65	84.4

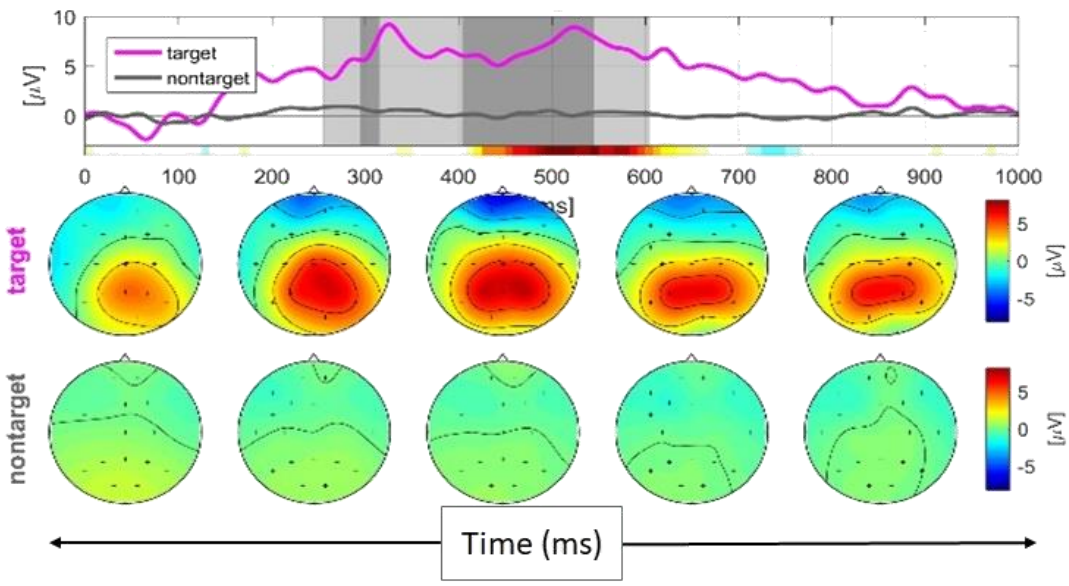

Fig. 7 ERP component of target and non-target plots for the subject. In each plot, the red and gray curves show target and non-target P300 component detection, respectively.

data in the second scenario (which the user did not pay attention to). Basically, if only the data of the second scenario are classified, it has no special meaning. The purpose of this classification is to evaluate how accurately the user's attention and inattention can be distinguished.

4 Conclusion

ERP is known to be very accurate in relation to the detection of visual stimuli. Using ERP, a novel method to test the focus of monitoring device operators such as operators for radars used in Navy ships was suggested. In this method, a Visual Stimuli was utilized to produce P300. As shown in the results section, the protocol used in this paper yielded an accuracy of up to 87% when the subject was paying attention. By implementing the method devised in this study, the focus of radar monitoring operators can be accurately deduced and even corrected considerably.

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