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Detection of Artifacts in Visual Evoked Potentials

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Abstract: The aim of this work is to introduce correlation test to detect artifacts in visual evoked potentials. If an artifact occurs a sample signal deviates from the ensemble average. In this paper signals with less correlation coefficient are considered as artifacts and are removed from the further analysis. An attempt has been made to apply these techniques to 14 -channel visual evoked potentials (VEPs) obtained from different subjects.

Keywords: evoked potentials, ensemble average, and correlation.

I. INTRODUCTION

Evoked potentials (EPs) or Event related potentials (ERPs) are voltage fluctuations within the Electroencephalogram (EEG) due to external stimulation or internal processes. Evoked potentials are usually considered as the time locked and synchronized activity of a group of neurons that add to the background EEG. An evoked potential (EP) is a signal that is generated as a result of the transmission of information induced by the application of a sensory stimulus to a sensory pathway. Examples of such stimuli are electric stimuli, visual stimuli, and auditory stimuli [26]. The application of a stimulus invokes a sequence of action potentials that is transmitted via a nervous pathway to the central nervous system (CNS). The activation of different parts in the nervous pathway leads to variations in the electromagnetic field that can be recorded on the scalp. Using surface electrodes a sequence of positive and negative peaks can be recorded; such a sequence is called a sensory evoked potential. These peaks are characterized by their amplitude and time after the stimulus, at which they occur the (post stimulus) latency. Evoked potentials are simultaneously recorded on the scalp with the spontaneous EEG. They are routinely used for clinical diagnosis, as they allow the identification of dysfunctions along the visual, auditory and somatosensory pathways. ERPs are also widely used in neuroscience research, given that the amplitude, latency and localization of different peaks or oscillatory patterns have been correlated to a large variety of sensory and cognitive functions.

The EEG signal has much larger amplitude than the evoked potential. EP is usually embedded in the ongoing electroencephalogram (EEG) and physiological artifacts with a poor signal-noise ratio (SNR) less than -6dB. This makes it difficult to estimate the EP. Therefore, the first aim of EP estimation is to enhance the poor SNR. As a result, various signal processing techniques have been developed to obtain improved EP from measured EEG. The conventional approach for EP estimation is to model as a deterministic function for repetitive stimuli, and ensemble averaging is employed to enhance the SNR[1]-[4]. This is required often hundreds of response trial to get a satisfactory estimate.

Evoked potentials are used extensively in the study of human brain functions and in clinical investigations to study normal and abnormal brain functions. They are used to test conduction in the visual, auditory, and somatosensory systems. During surgery they can be used to monitor the condition of structures at the operative site [30]-[32]. Fig.1. shows the placement of electrodes to record multi-channel evoked potentials.

Sensory evoked potentials can also be used for monitoring effects of anesthetics on the central nervous system (CNS). The choice of stimulus type to be used depends on the part of the nervous system to be investigated and the circumstances under which measurements are to be made.

Visual evoked potentials are very useful in detecting blindness in patients those cannot communicate, such as babies or animals. If repeated stimulation of the visual field causes no changes in EEG potentials then the subject's brain is probably not receiving any signals from his/her eyes. Other applications include the diagnosis of optic neuritis, which causes the signal to be delayed. Fig.2 (a) shows visual evoked potential recording setup where pattern reversal method is used as stimulus, and Fig.2 (b) shows a typical visual evoked potential.

Artifacts in EP waveform recordings typically result from voltage changes due to eye blinks, eye movements, muscle activities, and power line noise.

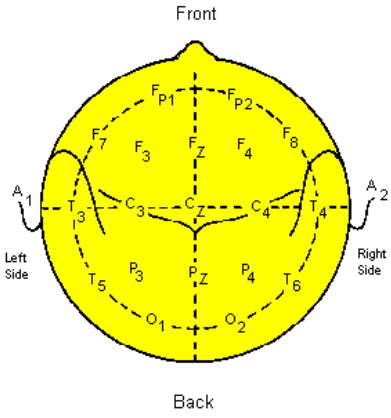

Fig.1. Placement of electrodes on the human scalp to record multi-channel evoked potentials.

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In real time, such artifacts can give inaccurate test results which can have serious consequences, such as inaccurate diagnosis in clinical evaluations [15] and [16].

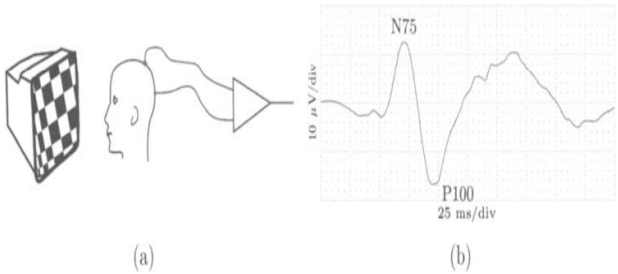

Fig.2. Visual evoked potentials. (a) Recording setup where pattern reversal method is used as stimulation and (b) typical VEP morphology.

Artifact detection in EPs is essential because artifacts are known to frequently occur in evoked potential data acquisition [13], [17], [20]-[22]. Recordings of evoked potentials were performed in an electrically shielded chamber in Voluntary healthy subjects (18–30 years old). Subjects were seated comfortably in a chair and were asked to remain still and relax while they did a visual and an auditory oddball paradigm.

Artifact detection strategy

We assure that, if an artifact occurs in one channel then the responses of all the channels are also artifacts. This assumption is valid as the EPs of neighboring channels are highly correlated. Therefore for a given trial, if an artifact is detected in any one or more channels, single trial data of all the channels for that trial are removed.

The three tests are described using $z_{m/c;n}$ to represent single trial EP n, $n = 1, 2, \ldots, N$, in the ensemble of class c, c = 1,2,…,C, recorded at channel m, m = 1,2,…,M. Where N is the number of single trial EPs in each ensemble, C is the number of brain activity categories, and M is the number of channels. The c-class ensemble of EPs collected at channel m will be referred to as m/c ensemble [12],[19],[24]and[25].

II. CORRELATION TEST

We can use correlation to compare the similarity of two sets of data. Correlation computes a measure of similarity of two input signals as they are shifted by one another. The correlation result reaches a maximum at the time when the two signals match best.

In signal processing, cross-correlation is a measure of similarity of two waveforms as a function of a time-lag applied to one of them.

For real discrete functions x(n) and y(n), the cross-correlation[7] is defined as

$$r_{xy}(l) = \sum_{n=\infty}^{\infty} x(n)\, y(n+l) \qquad (1)$$

Usually the signals of all channels and trials are to highly correlated. If an atifact occurs, the correlation among successive signals decreases. In this test we obtain the ensemble average of signals corresponding to all channels and trials. We identify the signals that are less correlated with the ensemble average as artifacts.

This test is described using $z_{m/c;n}$ to represent single trial EP n, $n = 1, 2, \ldots, N$, in the ensemble of class c, c = 1,2,…,C, recorded at channel m, m = 1,2,…,M. Where N is the number of single trial EPs in each ensemble, C is the number of brain activity categories, and M is the number of channels. The c-class ensemble of EPs collected at channel m will be referred to as m/c ensemble [8]-[13].

k^{th} sample of N – trial average evoked potential of each of the M channels is

$$Z_{m/c}(k) = \frac{1}{N}\sum_{n=1}^{N} Z_{m/c;n}(k),\ for \begin{cases} m = 1, 2, \ldots, M \\ k = 1, 2, \ldots, K \end{cases} \qquad (2)$$

Where $Z_{m/c;n}(k)$ is the k^{th} sample of n^{th} trial of m^{th} channel evoked potential in response to stimulus c.

Then k^{th} sample of N - trial, M - channel average evoked potential is

$$Z_c(k) = \frac{1}{M}\sum_{m=1}^{M} Z_{m/c}(k),\ for\ k = 1, 2, \ldots K \qquad (3)$$

The cross correlation of ensemble average Z_c with individual signals is given by

$$r_{m/c;n}(l) = \sum_{k=1}^{K} Z_c(k)\, Z_{m/c;n}(k+l),\ for \begin{cases} l = 1, 2, \ldots K-1 \\ m = 1, 2, \ldots, M \\ n = 1, 2, \ldots, N \end{cases}$$

Let $R_{m/c;n}(l) = \left| r_{m/c;n}(l) \right|$

Then $R(m,n) = \frac{1}{L}\sum_{l=1}^{L} R_{m/c;n}(l)$,

where L=2K-1 for m=1,2,…..M, n=1,2,……N

Let $\lambda_1 = \max[R(m,n)]$ and $\lambda_2 = \min[R(m,n)]$

and $d = median\left[R(m,n)\right]$

Let $d_1 = d - \lambda_2$, $d_2 = \lambda_1 - d$, $dd = d - d_2$

If the correlation cefficient of the samples of a single trial response $z_{m/c;n}$ in the m/c ensemble is less than the threshold ‘dd’ then nth single trials of all M channels are regarded as artifacts and are discarded from the m/c ensemble [14].

III. RESULTS

The median test was applied to 14-channel 71-trial VEP ensembles acquired from different subjects. The artifact detection strategy using correlation test was applied to 14-channel VEP ensembles acquired from different subjects. Fig.3, fig.4 and fig.5 shows a comparison of averages of actual evoked potential with average VEP after removal of artifacts using correlation test.

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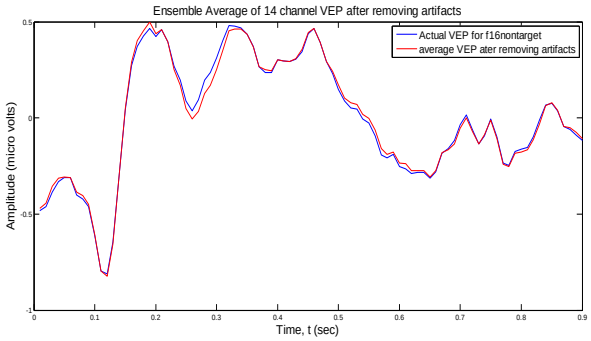

Fig. 3 Comparison of average VEP before and after removal of artifacts for subject f16nontarget

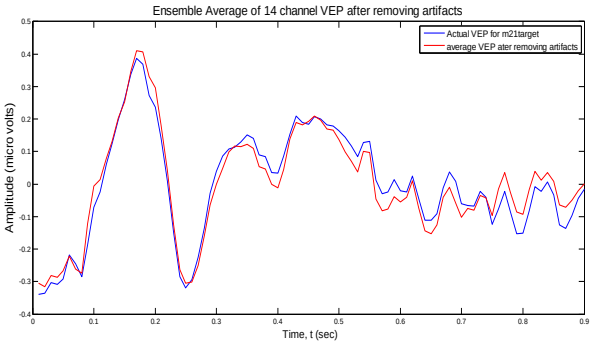

Fig. 4 Comparison of average VEP before and after removal of artifacts for subject m21target

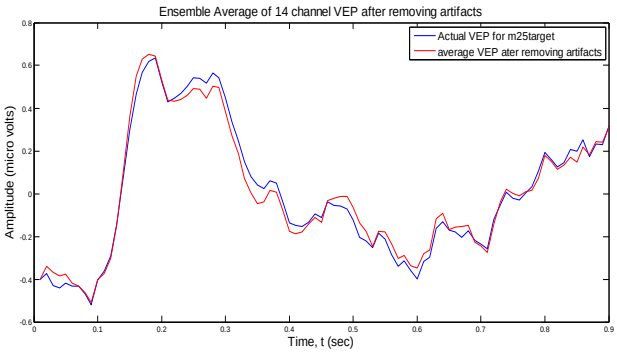

Fig. 5 Comparison of average VEP before and after removal of artifacts for subject m25target

IV. CONCLUSION

In this work artifacts are identified and rejected using correlation in acquisition of evoked potentials. This improves the peaks of average EPs and hence classifier performance.

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