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Visual Acuity Classification Using Single Trial Visual Evoked Potentials

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Abstract— **Several researches have been done to identify visual system characteristics. Some of them are based on the processing of the brain signal recordings. Visual evoked potentials (VEPs) are electrical signals which are produced in response to the visual stimuli and recorded by means of electrodes placed on the head. These signals are usually characterized by the amplitude and latency of their peaks. Different types of visual stimuli and visual system characteristics can affect the shape and hence the characteristics of VEPs. In this paper, proper visual stimuli were used and VEPs were recorded in order to classify visual acuity. To achieve this goal, visual evoked potentials were recorded and processed in time, frequency and time-frequency domains. In order to preserve dynamics of the recorded signals, two algorithms for single-trial VEP extraction were used. The results of the classification of visual acuity in both average and single-trial VEPs are acceptable.**

I. Introduction

SEVERAL researches have been done to identify visual system characteristics. Some of these methods are based on the processing of the brain signal recordings. Visual evoked potentials (VEPs) are electrical signals which are produced in response to the visual stimuli and recorded by the means of electrodes placed on the scalp. These signals are usually characterized by the amplitude and latency of their peaks. Different types of visual stimuli and visual system characteristics can affect the shape and hence the characteristics of VEPs. In these methods, usually the response of the brain system to a special visual stimulus is considered. Pattern reversal and pattern onset/offset stimuli which have more stable wave form are usually used in the clinical applications. Unlike behavioral methods, the VEP is not limited by lack of language comprehension, so it can be widely used for the eye examination of infants, children and disabled people [1], [2].

Due to the low amplitude of evoked potentials, they are typically obscured by the electroencephalogram (EEG), which is the spontaneous activity of the brain [3]. The traditional technique for extracting VEP from background EEG is ensemble averaging. However, this method requires many trials and does not allow the study of inter-trial information, amplitude and latency that change from trial to trial. Thus, for analyzing the dynamic of brain responses to sensory stimuli, it would be better to use single trial analysis.

In this paper, we tried to classify the visual acuity of the subjects to two groups of (near-) normal and low vision using visual evoked potentials. To achieve this goal, visual evoked potentials were recorded and processed in time, frequency and time-frequency domains. In order to preserve the dynamics of the recorded signals, two algorithms for single-trial VEP extraction were used and both the average VEP and single trial one were used for visual acuity classification.

The rest of this paper is organized as follows. In section II, a brief discussion about visual evoked potentials is presented. Section III presents two algorithms for single-trial VEP extraction. In the next section the data acquisition system is introduced. Feature extraction and classification methods are presented in section V. To evaluate the efficiency of our experiments, we will show the result of these methods in section VI.

II. Visual Evoked Potential

The VEP which is usually the response of the brain to light flashes or visual patterns is recorded form the scalp over the occipital lobe. The amplitude of the VEP varies from 1 to 20 μV with a bandwidth of 1 to 300 Hz [1], [4].

According to the visual evoked potential standards [5], the VEP is an evoked electrophysiological potential which can be extracted using signal averaging, from the electroencephalographic activity recorded at the scalp. The current standard presents basic responses elicited by three commonly used stimulus conditions: pattern reversal, pattern onset/offset and flash stimuli. In this paper only the pattern stimuli were used [5].

The pattern reversal stimulus consists of black and white checks that change phase (i.e. black to white and white to black) abruptly and repeatedly at a specified number of reversals per second. The luminance of the screen should not be changed. Each pattern stimulus should be defined by the visual angle subtended by the side of a single check, the reversal frequency, the number of reversals, the mean luminance, the pattern contrast and the field size [5].

For pattern onset/offset, a pattern is abruptly exchanged with a diffuse background. The same parameters as pattern reversal stimulus must be defined for this stimulus [5].

The typical response of an adult aged 18–60 years to the pattern stimuli is almost unchanged. Fig. 1 (a) shows the pattern reversal VEP, which consists of N75, P100 and N135

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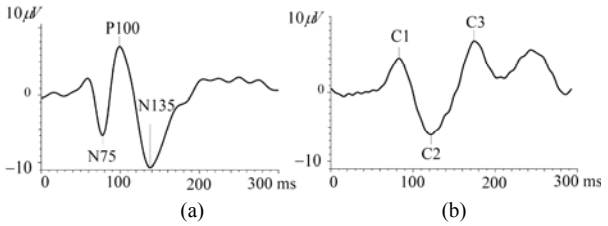

Fig. 1. The typical response to the (a) pattern reversal stimulus and (b) pattern onset/offset stimulus [5].

peaks. It has relatively low variability of waveform and peak latency both within a subject and over the normal population. P100 peak latency is affected by non-pathophysiologic parameters such as pattern size, pattern contrast, pattern mean luminance, refractive error and poor fixation [5].

The waveform of pattern onset/offset VEP is shown in Fig. 1 (b). The onset /offset VEP is more variable in appearance than the pattern reversal VEP. It typically consists of three main peaks in adults; C1 (positive approximately 75 ms), C2 (negative approximately 125 ms) and C3 (positive, approximately 150 ms) [5].

III. Single Trial Evoked Potential Extraction

Due to the low amplitude of evoked potentials, the common technique of extracting EP from background EEG is ensemble averaging which eliminates inter-trial information. Thus, for analyzing the dynamic of brain responses to sensory stimuli, it would be better to use single trial analysis. In this section, two methods of extracting single trial evoked potentials are examined.

A. Autoregressive Model with Exogenous Input

Parametric methods have been employed mostly to filter evoked potentials. Among these models, autoregressive model with exogenous input (ARX) shows good performance in EP extraction.

By using the hypothesis of additivity of the stimulus-related and stimulus-unrelated activities in evoked potentials, the signal recorded after a visual stimulus may be described as follows [6]:

$$x_i(t) = c_i(t) + n_i(t) \quad (1)$$

where i indicates the ith response, $c_i(t)$ is the activity elicited by the stimulus and $n_i(t)$ is the background electroencephalographic not related to the stimulus. The noise $n_i(t)$ may be viewed as the output of an autoregressive model driven by a white noise $e_i(t)$. The evoked response $c_i(t)$ is instead modeled as the output of an autoregressive-moving average filter of a known signal $u(t)$. Its characteristics should be similar to the ones of the evoked response under analysis, which is usually chosen as the average of a sufficient number of sweeps, recorded from the same subject.

Thus, the mathematical form of the model becomes [6]:

$$x_i(t) = -\sum_{j=1}^{p} a_j\, x_i(t-j) + \sum_{j=d}^{q+d-1} b_j\, u(t-j) + e_i(t) \quad (2)$$

where p, q and d are the orders of the autoregressive and the moving average part and the temporal delay respectively.

The parameters of the model can be identified by minimizing the function J:

$$J = \frac{1}{N}\sum_{t=1}^{N}[e_i(t)]^2 \quad (3)$$

where $e_i(t)$ is the difference between the recorded signal $x_i(t)$ and the signal estimated by the model $\hat{x}_i(t)$:

$$e_i(t) = x_i(t) - \hat{x}_i(t) \quad (4)$$

Then, the single evoked responses were filtered by the means of this model [6].

B. Iterative Generalized Eigen Value Decomposition

One of the recent algorithms to extract single trial evoked potential is iterative generalized eigen value decomposition (iGEVD) [7]. In this algorithm, by describing $x(t)$ as an array of L single trial responses and $x_{average}(t)$ as the average signal, signal and non-signal covariance matrices can be defined as follows [8]:

$$A = E\{x(t)x(t)^T\} \quad (5)$$

$$B = E\{\Big(x(t) - x_{average}(t)\Big)\Big(x(t) - x_{average}(t)\Big)^T\} \quad (6)$$

By the joint diagonalization of the matrix pairs (B,A), signals can be decomposed to components ranked according to their resemblance with the VEP signal.

So, the iGEVD algorithm which is applied to a set of recordings consisting of L single trials is as follows:

1. Compute an average VEP from L single trials.
2. Calculate covariance matrices A and B using (5) and (6).
3. Apply generalized eigen value decomposition on the covariance matrices A and B and extract uncorrelated sources.
4. Compute the absolute correlation value between the sources and average VEP (temporal correlation).
5. Compute spectrogram for each single trial and each source.
6. Calculate 2-dimensional correlation coefficient between the spectrogram of each pair of single trials and sources within a predefined window W_{th} (spectrogram correlation).
7. Set to zero those sources with temporal correlation less than a predefined threshold T_{th} and spectrogram correlation less than S_{th}, for each single trial.
8. Compute the inverse transform of the updated sources back to the time domain, separately for each single trial.
9. Repeat steps 1 to 8 until a convergence criterion (which is mentioned in [7]) is met.

IV. Data Acquisition

In our experiments, the electric brain activity was measured using an EEG system (Powerlab/16sp, ADInstrument, $F_S = 1kHz, Z_{in} = 200\ M\Omega, CMRR = 76dB$) in Biomedical Laboratory, Electrical Engineering department, Sharif University of Technology. According to the fact that this system is not designed for VEP recordings, the additional circuit was used for synchronizing stimuli and VEP recordings.

TABLE 1
THE USED PARAMETERS IN THE EXPERIMENTS

Distance from monitor	Pattern element size (checks) (min)	Visual field (deg)	Mean luminance ($cd.m^{-2}$)	Contrast (%)	Presentation rate	Number of presentations
1 m	60, 15	16	50	85%	1 Hz	80

A total of 17 adults (9 women and 8 men, ages 18-32) were examined in this study. The eye examination was done on each subject by two ophthalmologists and the visual acuity was measured for them. The subject's visual acuity varies from 10/10 to lower than 1/10. All the subjects with an abnormal acuity suffered from myopia or astigmatism and the visual acuity after removing refractive error was 10/10 for all of them.

For each eye four experiments were done: two pattern reversal and two pattern onset/offset stimuli using 1 deg and 15 min per side checks. All the experiments were monocular recordings. Other parameters used in the experiments are shown in Table. 1.

V. METHODOLOGY

The recorded VEPs were used to classify visual acuity to two groups: (near-) normal (VA>0.3) and low vision (VA<0.3) [9]. To achieve this goal, three signals were extracted from each trial: Average-VEP, single trial VEP extracted using ARX model and single trial VEP extracted using iGEVD method. From each signal different features were extracted and the classification procedure was applied on them. In this section, this method is described in detail.

A. Pre-Processing

First, by using recorded EOG channel, single trial recordings which were synchronized with blinks or motion artifacts were removed. Then 0.9-110 Hz band pass filter and 50 Hz and 100 Hz notch filters were used for noise reduction. Using these filtered signals, Average-VEP and single trial VEPs (using ARX model and iGEVD method) were generated.

B. Feature Extraction

The primary features utilized in the proposed algorithm can be classified into four groups: morphological, statistical, frequency domain and time-frequency domain features, which will be explained in detail. In the feature definition, $x(t)$ and $P(w)$ represent signal in time domain and its power density respectively. It should be mentioned that each feature was calculated for every three types of VEP and for all recordings.

1. ***Morphological Features:*** The clinical applications of VEPs are usually based on simple morphological features, such as amplitude and latency of main peaks of the signal. So, the first group of the used features which are inspired from [10] are as follows:

-- Latencies of the main peaks
-- Peak to peak amplitude of the main peaks
-- Total absolute area
-- Average absolute signal slope
-- Peak to peak slope
-- Slope sign alterations

According to the waveform of the recorded signals, three main peaks N75, P100 and N135 for pattern reversal VEP and two peaks C2 and C3 for pattern onset/offset VEP were considered.

2. Statistical Features: Statistical features have useful information of the signal waveform which can be used for signal processing. Some of them which are used in this paper are as follows:

-- Variance
-- Number of zero crossing
-- Amplitude histogram
-- Autoregressive model coefficients
-- Form factor which is determined by [11]:

$$\frac{\sigma_{\ddot{x}}/\sigma_{\dot{x}}}{\sigma_{\dot{x}}/\sigma_{x}} \tag{7}$$

where $\dot{x}$ and $\ddot{x}$ represent first and second derivatives of the signal respectively, and σ_x^2 is the statistical variance of x .

3. Frequency Domain Features: The frequency domain features are as follows [12]:

-- Mode frequency
-- Mean frequency
-- Median frequency
-- Signal's energy in different frequency bands: 2-8, 9-15, 16-22, 23-29, 30-36, 37-43 and 44-50 Hz.

4. Time-Frequency Domain Features: The coefficients of discrete wavelet transform with the Quadratic B-Spline mother wavelet were calculated in 7 scales [10]. Then the coefficients of approximation (c0) and 3 levels of details (d0; d1; d2) were used as the time-frequency domain features. For the used signals with 1000 Hz sampling rate, these bands were 0-3.5Hz, 3.5-7.5Hz, 7.5-15 Hz and 15-30 Hz which are almost equivalent to standard delta, theta, alpha and beta bands.

C. Classification

The classification procedure was done four times for each group of features separately and one time for all of the features. As it is mentioned above, for every three types of VEP, the classification was done and the classification accuracy was calculated separately.

According to the few number of trials (34 trials, 2 eyes of every 17 subjects), the leave one out (LOO) method was used. The linear SVM classifier was utilized for classification of the normalized feature vectors. To determine SVM parameters, cross-validation was used on the training data.

VI. Results and Discussion

By applying the proposed method on the recorded VEPs, the accuracy, sensitivity and specificity of classification of visual acuity to two groups of (near-) normal and low vision were calculated. Fig. 2, Fig. 3 and Fig. 4 show the classification accuracy, sensitivity and specificity of the LOO method for every three types of VEPs on different feature groups respectively.

According to the results, the best accuracy of 82.3% was achieved by iGEVD single trial VEP on the wavelet feature group. Also, the best sensitivity was 86.7% which was obtained by a similar VEP on statistical, wavelet and all features groups. Using Average-VEP on morphological feature group, the best specificity (84.2%) was achieved.

By comparing the results of the methods of extracting single trial VEP with each other, it can be seen that using single trial VEP extracted by iGEVD method generates better accuracy and sensitivity in almost all feature groups. But the specificity graph (Fig. 3) shows no difference between these two methods on average.

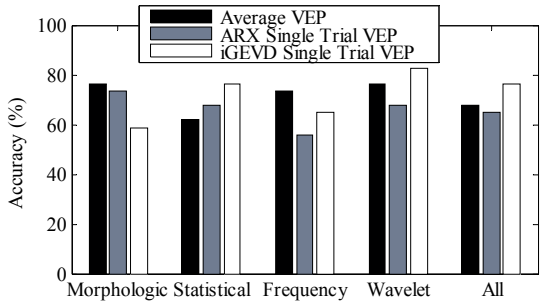

Fig. 2. The classification accuracy for every three types of VEPs on different feature groups.

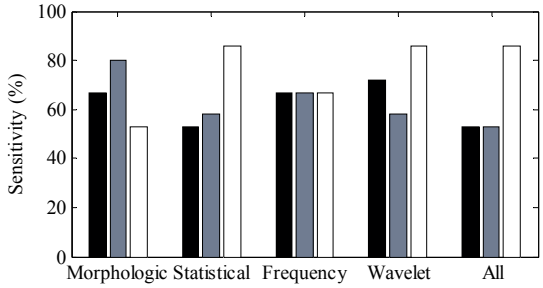

Fig. 3. The classification sensitivity for every three types of VEPs on different feature groups.

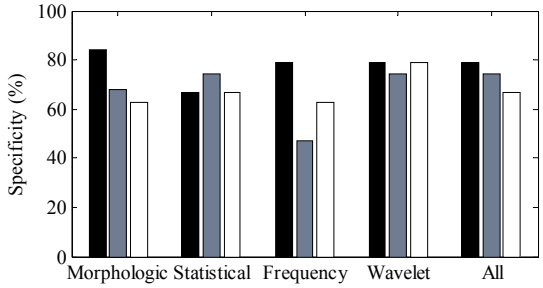

Fig. 4. The classification specificity for every three types of VEPs on different feature groups.

Also, the results of using this method show better classification accuracy and sensitivity in comparison with the Average-VEP method on average. This result is not correct for the classification specificity. Also, it can be seen that the wavelet feature group generates better results among all feature groups, by using single trial VEP extracted by iGEVD method and Average-VEP.

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