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Application of clustering techniques for visually evoked potentials based detection of vision impairments

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ABSTRACT

Visually evoked potentials (VEP) are evoked responses of the brain corresponding to a specific visual stimulus. Ophthalmologists often refer their patients to VEP test if the latter suffers any vision abnormalities that cannot be diagnosed using conventional analysis. By investigating the VEP responses, medical experts can narrow down the possible cause of the defect. Although this method provides valuable information to the medical practitioner, there are several drawbacks of the analysis that can affect the diagnosis result. The conventional averaging of the signals results in inter-trial variation between the VEP responses to be lost. This method also requires large number of trials, which causes fatigue in patients and reduces the diagnostic accuracy. Therefore, we have proposed a new method of analysis using statistical features derived from time and spectral space for the discrimination of vision impairments. Feature enhancement methods such as feature weighting and dimensional reduction are used to enhance the statistical features prior to the analysis. Four clustering methods are employed to increase the interclass separability of the control and myopic features while reducing the within class variability. The dimension of the weighted features is reduced using a combination of principal component analysis (PCA) and independent component analysis (ICA) techniques prior to classification. The proposed method is able to achieve 100% accuracy using extreme learning machine (ELM) and multi layer neural network (MLNN) classifiers.

1. Introduction

Visually evoked potentials (VEP) are electrical signals induced by the occipital cortex as a response to visual stimulus presented and are extensively being studied for the detection of visual abnormalities. The VEP recordings are done non-invasively, using electroencephalogram (EEG) electrodes that are placed over the scalp overlaying occipital cortex. The VEP test is often useful in patients suffering loss of vision due to

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Table 1 – Summary of VEP analysis.

Author/year	Nature of study	Subjects	Contributions/findings	Classification accuracy
A. Ademoglu (1997)	Studied VEP in demented subjects using Spline wavelets	24 normal 16 demented	Reported that (N70–P100–N130) complex falls in delta-theta band.	–
Quian Quiroga (2001)	EEG, ERP study using Quadratic Spline wavelet approach	9 normal	Reported that P100 falls in alpha-theta band, while P300 response is found in delta region	–
K. Momose (2005)	VEP in color vision defectives	5 deuteranope 4 deuteranomalia 8 normal	Suggests iso-luminant chromatic gratings efficient in detecting color abnormalities. Proposed investigating SNR of 10 log (VEP at 12 Hz/VEP at 16 Hz) for indication of abnormalities	–
Aysegul Guven (2008)	VEP analysis of vision impairments	61 normal 68 pathological	Stressed the effectiveness of GDA preprocessing method for VEP classifications.	5 classifiers, 93.86%
Kemal Polat (2008)	VEP analysis of vision impairments	61 normal 68 pathological	Proposed using the discretization method for VEP classifications.	3 classifiers, 100%
V. Vijean et al. (2013)	VEP analysis of vision impairments	8 normal 8 myopic	Found statistical features are effective in discriminating vision impairments	2 classifiers, 96.89%

injuries along the visual nerve pathways. By relying on their medical expertise, the ophthalmologist is able to diagnose the abnormalities using averaged VEP responses. A minimum of 64 trials is averaged to get the final waveform for the analysis. This method however, has several disadvantages such as loss of inter-trial variations, stationary signals assumptions and requirements for large number of trials [1,2]. Therefore, researchers are now focused on developing alternate analysis method for characterizing the VEP signals. A concise summary of significant research works in literature [2–7] for VEP studies are given in Table 1.

From Table 1, it can be observed that although all these researches have contributed significant findings to the VEP analysis, the development of signal processing algorithms for investigation of vision impairment is still at its infancy. Therefore, we have focused on improving the performance and computational cost of our existing VEP signal processing algorithm [7] in this study by employing new feature enhancement techniques. Four clustering based feature weighting techniques are suggested to increase the interclass variation of the time and spectral features and principal component analysis (PCA), independent component analysis (ICA) and PCA + ICA techniques are used to reduce the dimension of the weighted features. The preprocessed features are then classified into normal and vision impaired (myopic) by extreme learning machine (ELM) and multi layer neural network (MLNN) classifiers.

2. VEP recording procedures

The experimental protocol for the VEP recordings are designed in compliance with the standard guidelines established by the International Society for Clinical Electrophysiology of Vision (ISCEV) [8] and is approved by an experienced ophthalmologist. The monocular VEP recordings are done in a dark, sound attenuated room. The responses are recorded non-invasively from 16 eyes of 10 subjects using electroencephalogram (EEG) gold plated surface electrodes. The controls are selected from subjects with visual acuity of 160/200 or better and myopic with visual acuity of 60/200 or worse. The one degree pattern reversal black and white checkerboard stimulus is presented to the subject using a HP L1908w LCD monitor at 0.5 Hz and the VEP responses are recorded using g.BSamp bioamplifier. The subjects are required to fixate on the red fixation point at the center of the screen while the recordings take place. Samples are recorded at a rate of 1 kHz from Oz, O1, and O2 positions that are referenced to Fz and grounded at Cz according to international 10–20 system. A total of 1260 normal and 1236 myopic VEP responses are recorded and used in the analysis.

3. Preprocessing and feature extractions

The raw traces of single trial VEPs are pre-filtered using 100 μV rejection criteria to remove the eye blink artifacts [9]. The pre-stimulus baseline is set to zero by means of removing the mean from the samples.

The preprocessed VEP signals are decomposed into *delta* (0.5–4 Hz), *theta* (4–8 Hz), *alpha* (8–16 Hz), *beta* (16–32 Hz), *gamma1* (32–64 Hz) and *gamma2* (64–128 Hz) bands using an elliptic filter with 20 dB minimum stopband attenuation and 0.1 dB maximum passband ripple. Forward and reverse filtering is applied to eliminate non-linearity of the digital filter. Four different features, *standard deviations* (*Std*), *entropy*, *power* and *energy* are extracted from the decomposed signals using a 0.5 s time frame. The time domain features are extracted directly from the decomposed signals, while the spectral features are obtained through fast Fourier transformed waveforms. The mathematical equations for the features are shown in Eqs. (1)–(4).

$$Power = \frac{1}{n}\sum_{i=1}^{n} x_i^2 \quad (1)$$