EXCELLENT PUBLISHERS

International Journal of Current Research and Academic Review

ISSN: 2347-3215 Volume 2 Number 11 (November-2014) pp. 51-58

www.ijcrar.com

Effective classification of occlusion therapy with single trial P-VEP signals for squint eyes

R.Kalaivaazhi[1]* and P.Balamurugan[2]

[1]Department of Information Technology, Anjalai Ammal Mahalingam Engineering College, Kovilvenni, Thiruvarur (DT), Tamilnadu, India

[2]Mounzian College of Engineering, Pudukottai, Pudukottai(DT), Tamilnadu, India

Corresponding author

KEYWORDS

P-VEP,
Occlusion therapy,
Neal stimulus,
Cross validation,
Classification accuracy.

A B S T R A C T

P-VEP was used to observe the human visual perception process such as pattern reversal of check board. This paper examines the possibilities of classifying the effectiveness of the occlusion therapy when viewed by checker board pattern reversal process in single trial using single channel P-VEP wave forms of the frontal area (F_z) and occipital area (O_z) of the brain. The first 10 trials were used for calibration, and the remaining trials were assigned to test data set. Feature vectors for each trial were created as P-VEP, 100 msec up to 800 msec after the stimuli was shown. To extract features of waveforms, the regression relationship between EEG and P-VEP waveforms was used to transform observed signals. As a result, the performance of cross validation rates of the test data set increased incrementally during the pattern reversal process for both F_z and O_z. The predicted waveforms were measured using regression relationship. Also the effectiveness of predication using the regression relationship for the classification performance of the occlusion therapy was determined. This provides evidence that a procedure using relationship between EEG and P-VEP is effective in predicting occlusion therapy.

Introduction

Evoked potentials are small electrical events arising from neural tissue occurring in response to abrupt sensory stimulation. In current clinical application this usually involves stimulation of the visual or auditory system. Stimulation to elicit a visual evoked potential requires light with abrupt onset, such as a stroboscopic light or an array of light emitting diodes (LEDs).

Flash evoked responses consist of a number of positive and negative peaks that vary greatly between individuals and are affected by subtle changes in the level of arousal and parameters of stimulation. This variability has limited their clinical utility. However, they are helpful in assessing patients whose visual acuity is too poor to generate evoked potentials to pattern reversal and in testing comatose patients and others unable to fixate on the pattern stimulus. Changes in the latencies and morphology of the responses have been used to follow the course of hydrocephalus both before and after shunting, with improvement in the flash evoked potentials. When shunting is successful and regression of the expected maturational change in the response, if shunt failure occurs, the absence of a response is indicative of poor or absent visual function, and failure to record such responses in children usually indicates a poor prognosis for visual development.

The aim of this paper is to examine the effectiveness of occlusion therapy, using single-channel single-trial P-VEPs in response to the pattern reversal process. This process takes into consideration the activities in the frontal and occipital areas of the human brain. The effectiveness of a single prediction technique with support vector regression [SVR] using a relationship which is based on the regression between EEG & P-VEP was measured. In particular, the possibility of classification using single channel P-VEP wave-forms will be addressed. The overall performance was evaluated for its accuracy and the performance changes were discussed, with adequate consideration given to the occlusion therapy process. The degree of individual difference was also considered to determine the possibility of applying this technique to the classification of the effectiveness of occlusion therapy.

Method

In this section, new procedures for estimating the effectiveness of occlusion therapy observed by users using single - channel and single-trial P-VEP waveforms are summarized. To observe P-VEP waveforms during the perception process, Neal stimulus recognition task was conducted (Abe and Nakayama, 2006a; Abe and Nakayama, 2006b). The experimental task is depicted in Figure 1(a). Symbol was flashed on a computer screen, P-VEP waveforms were recorded from 21 electrodes, as shown in Figure 1(b).

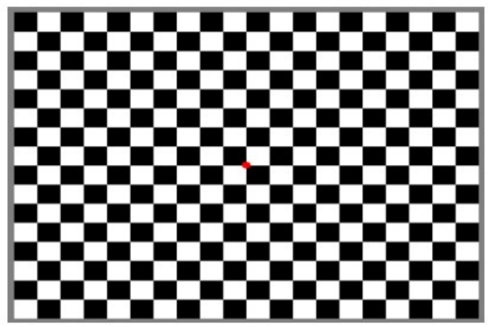

Fig 1 (a) Checkerboard pattern with red fixation point

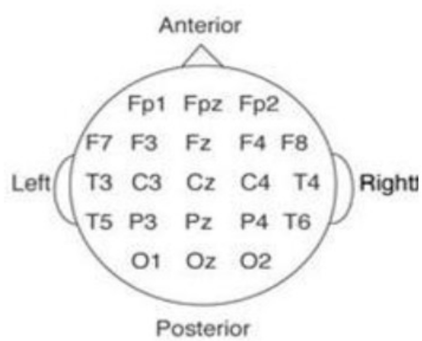

Fig 1 (b) Placement of electrodes

A reference electrode usually placed on the earlobe, on the midline on top of the head or on the forehead. Ground electrode can be placed at any location. The time period analyzed is usually between 100 and 500 milliseconds following onset of each visual stimulus. When testing young infants, analysis time was 300 msec or longer because components of the P-VEPs may have long peak latencies during early maturation. Most adults were tested using an analysis time of 250 msec or less. The most common amplifier band pass frequency limits are 1 Hz and 100 Hz. Amplifier sensitivity settings vary with ± 10 μV common for older children through adults and ± 20 to 50 μV for infants and younger children. Sometimes the sensitivity setting must be changed to accommodate larger P-VEP voltage in all age groups. See the ISCEV (International Society for Clinical Electrophysiology of Vision) standard for clinical P-VEPs for variety of recommended test protocols. Commonly used visual stimuli are strobe flash, flashing light – emitting diodes (LEDs), transient and steady state pattern reversal and pattern onset/offset.

The most common stimulus used is a checkerboard pattern, which reverses every half second. Pattern reversal is a preferred stimulus because there is more inter - subject P-VEP reliability than with flash or pattern onset stimuli. Camera shutters on each projector controlled the display of each checkerboard reversing at a rate 2 per second.

This experiment examined the Neal stimulus recognition process in accordance with the differences in P-VEP waveforms among Neal stimulus which were known, and unknown. The number of trials for each kind of stimuli was 100. For each subject, a total of 200 trials were analyzed. The procedure was as follows: (1) The subject clicked the left button of a mouse to start the trial. (2) A black screen which gave a random delay of half second was then presented. (3) Fixing of red dot on screen (either a known Neal stimulus or an unknown) was presented briefly (500 msec). (4) The subject had to report if the fixing of red dot presented was a known Neal stimulus or unknown by clicking the mouse's left or right button respectively. Four subjects who were 7–13 years old participated in this experiment.

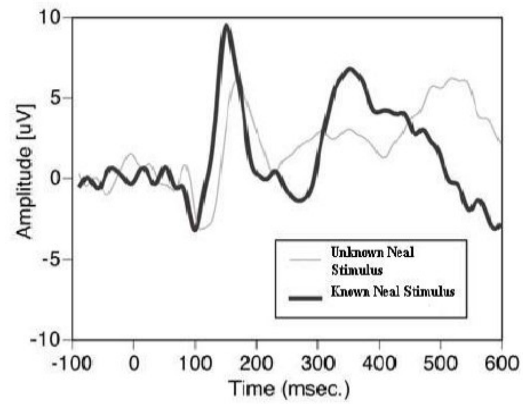

Fig.2 P-VEP waveforms from Fz electrode

Figure 2 shows P-VEP extracted from the Fz electrode. The waveforms of all correct responses were summed up, and compared with P-VEP waveforms of known and unknown Neal. These P-VEP waveforms are well smoothened and show the differences in response to the stimuli. Some significant differences between known and unknown Neal were observed in P100 (at 100 msec.), N170 (at 170 msec.) and P250 (at 250 msec.) on Fz and Oz. Mean reaction time was around 500 msec., and the waveforms between 100 and 500 msec. were significantly different because the recognition processes were different.

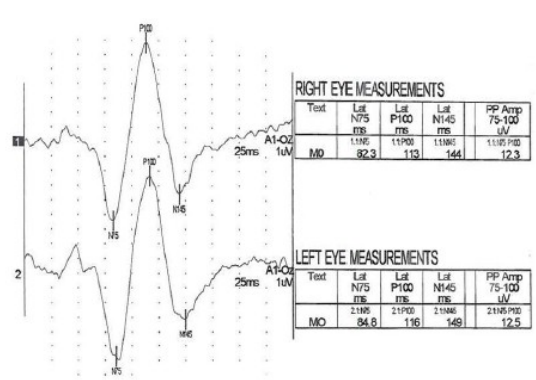

Fig.3 P-VEP record from 12 yr old patient

In this paper, we focused on single-channel P-VEP waveforms for known and unknown Neal stimulus measured at the Oz and Fz electrode, because the occipital area reflects visual perception and the frontal area reflects the discrimination process. The differences in waveforms are evaluated using signals from electrodes near each area of the brain. Figure 3 shows a sample recorded wave form for 12 year old patient.

Classification of single – trial P-VEPs

The classification performance for single-trial P-VEP waveforms from the Oz and Fz electrodes were evaluated for the effectiveness of occlusion therapy. Therefore, only trials with correct responses were selected. All P-VEP waveforms for each subject were smoothened in advance, to permit the application of some signal processing. The first 20 trials, which showed both known and unknown Neal, were used to create a training data set for each subject. A test data set was then created using the remaining data.

Classification without predictions

For the training data, classification labels were given to each data set. These data sets contained significant response periods, which were controlled to be from 100–150 msec (for 26 data points) to 100–500 msec (for 205 data points) long. The duration was extended step by step, by 100 msec up to 500 msec. From 500–800 msec (for 153 data points) data was collected.

Here, ai is defined as an P-VEP potential, *t* is defined as the stimulus given, and the training data set comprises M input vectors a = (a1 …….. aM) with corresponding target values: *t* = {-1 unknown, +1 : known Neal }. The acquired data can be noted as (a, *t*) for each trial. A sign function, based on the SVM function, is defined as function *G* using the Gaussian kernel. For every interval, the parameters for the Gaussian kernel were optimized using a software tool (Chang and Lin, 2009). The classification was conducted using SVM with Gaussian kernel, such as LIBSVM (Chang and Lin, 2009).

After the training procedure was completed, the test data set was classified. The prediction class *t*ˆ is given as *t*ˆ = *G*(a) for the test set, and the rates for correct prediction (*t* vs. *t*ˆ) are evaluated across the duration of the interval. This classification procedure is called “NO-REG” in response to the following procedure.

Classification with Event -Related Potential (ERP) references

To extract the relationship between P-VEP and ERP, ERPs for unknown and known Neal respectively were extracted from the training data set of each subject. Because the training data set consists of trials which show both unknown and known Neal, the relationship is formulated as a regression function across both P-VEP responses. Therefore, the regression prediction from a single-trial P-VEP waveform may reflect both ERP features of unknown and known Neal. To predict an appropriate signal in response to ERP waveforms from observed P-VEP signals, a regression function from a single-trial EEG to ERP has been created, using the Support Vector Regression (SVR) technique. This regression training procedure was conducted on a training data set, which consisted of P-VEPs of both unknown and known Neal for each subject. Two prediction procedures were created in this study, as follows:

Regression prediction (REG)

Raw data signal is used for prediction. The regression function f was created for the training set. Here, ai is defined as P-VEP potentials, and yi is defined as an ERP which sums up P-VEP waveforms of all trials in the training data set. The estimated ERP yˆ k for the empirical potential yk at the time position k is reproduced from time series data samples comprising 10 input vectors a*k* , so that a *k* = (a k-9 ….. ak), *y*ˆ k = f (ak).

The parameters of SVR were given as a standard deviation for Gaussian kernel and as a width of error pipe (epsilon: *eps* = 0.5) using SVM Torch (Collobert, 2008; Collobert and Bengio, 2001).

The relationship between the viewed character class *t* and the estimated ERP yˆ also can be noted as (t, yˆ) for each trial, in both the training and test data sets. Both classification training and testing use the same procedures, and use the above classification without predictions as well.
This procedure can be applied to online processing. Once the regression and classification functions have been created from the training data set, EEG waveforms for consequent trials are estimated and the character believed to have been viewed is predicted, step by step.

Standardized regression (STD-REG)

All EEG waveform data for training and test data sets are standardized using the overall means and "REG". This procedure cannot be applied to any novel trials. This post processing may neglect the differences between trials for some subjects. Therefore, this processing can be referred to as an off-line classification.

Result and Discussion

The performance of cross validation rates of the test data set and the effectiveness of the prediction using the regression relationship for classification performance were determined during the perceptual process.

Cross validation rate

The ability of classifying the test data was assessed as a cross validation rate using LIBSVM (Chang and Lin, 2009). In this procedure, the test data set was randomly divided into 5 blocks and the performance of classifications was assessed. The rates were calculated for each subject and the mean rates across the three classification procedures were summarized. The results for the Oz electrode are summarized in Figure 4.

The horizontal axis shows the duration and the vertical axis shows the cross validation rate. The "NO-REG" shows the results using raw observation data. The rate increases gradually with the extension of the duration, and the highest rate is during duration of 100-500 msec. This rate is significant using a non-parametric test (Shiba and Watabe, 1976), but other rates are not significant except in a condition with duration of 500-800 msec.

When predicted P-VEP waveforms were applied to classifications such as "STD-REG" and "REG" all rates were significant except for conditions with duration of 100-150 and 100–200 msec. In particular, data for a duration of 100–300 msec. became significant when the estimated EEG waveforms were applied using the regression function.

This duration includes P100, N170 and P250, so that predictions using the regression relationship between P-VEP and ERP may emphasize the differences in waveforms. This also suggests that the data for duration of 100-200 msec is insufficient for its classification.

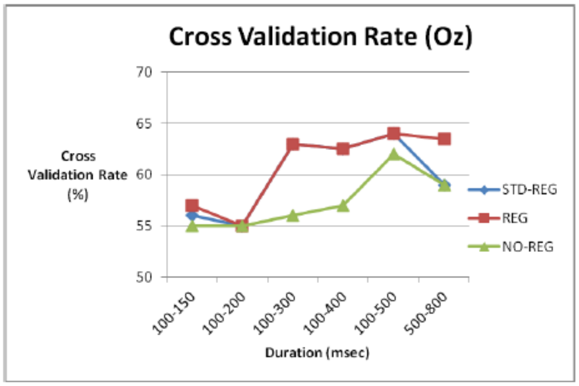

Fig.4 Cross validation rate (Oz)

The results for FZ electrodes are summarized in Figure 5. The highest performance classification was for duration of 100-500 msec across the three processing conditions. For this duration, "STDREG" is the highest, and "REG" is higher than "NOREG". The performance with predictions using the regression relationship is almost always higher than the performance with raw observed data across all durations. For durations up to 400 msec all rates are not significant; however the rate with predictions is almost always higher.

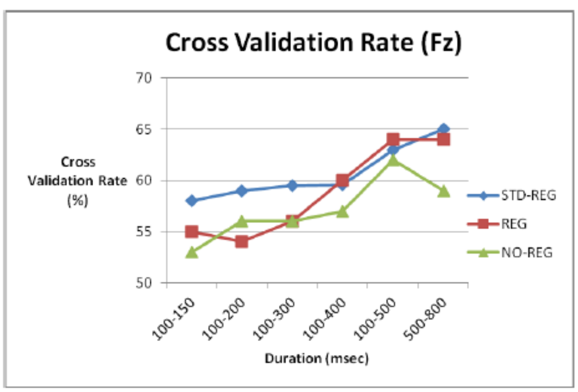

Fig.5 Cross validation rate (Fz)

In comparing the results for Oz and Fz, the duration for the highest rates are different. For the Oz classification, predicted waveforms up to 300 msec are sufficient, and predicted waveforms up to 500 msec are required for Fz classification. Both classification results suggest that P-VEP waveforms before the button was pressed to make a selection (around 500 msec) reflect the viewed characters specifically. From this, it can be determined that single-trial P-VEP waveforms contain significant information in response to checker board pattern reversal.

In general visual information processing theory, the retinal image is mapped in the primary visual cortex, which is located in the occipital area (Posner and Raichle, 1994). During the decision task, some activation may be observed on the frontal cortex, which is located in the frontal area. Some time is needed to recognize, resulting in the highest perception by Fz as compared to Oz coincides with the chorological model, but the measured time of the delay seems longer than in theory.

Therefore, some factors may influence the cross-validation rates in addition to influencing the image processing pathway. For Fz classification with prediction using waveforms up to 200 msec. the improvement of rates may suggest that some features of waveforms have been emphasized by the relationship between P-VEP and ERP even in the earlier part of the period prior to recognition, though the rate is not significant. These results suggest that predictions using the relationship between P-VEP and ERP are effective.

Classification accuracy

The classification performance for the Oz electrode is summarized in Figure 6. Again, the classification model was prepared using the training data set which consisted of the first 20 trials. The model was then applied to the test data set. The rates of classification accuracy increase from the duration of 100-150 msec to 100–400 msec and the rates for 100–400 msec are the highest. The rates for both 100–400 msec and 100–500 msec are significant.

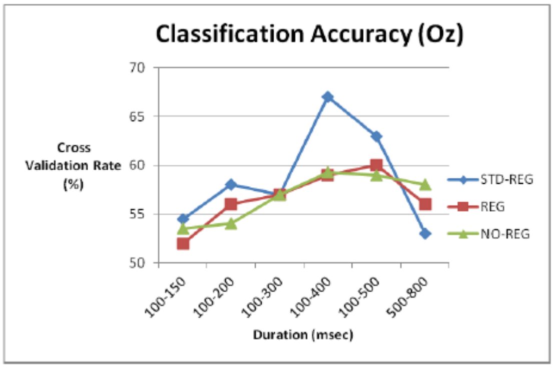

Fig.6 Classification accuracy (Oz)

During these periods, the rate for "STD-REG" is the highest across the three conditions. The regression processing of the raw data may not be effective for the classification of Oz waveforms. The standardized processing has a significant effect on the duration from 100-400 msec as the rate has improved dramatically.

This suggests that the deviation of waveforms influences the rate. Fz classification performance is summarized in Figure 7. The highest levels of classification accuracy are different across the three conditions: 100–400 msec for "STD-REG", 100-500 msec for "REG", and 500–800 msec for "NO-REG".

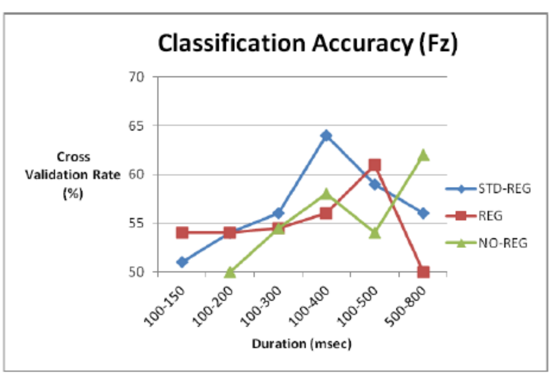

Fig.7 Classification accuracy (Fz)

When the classification was conducted using standardized and predicted waveforms, earlier waveforms of between 100 and 400 msec are effective. For predicted waveforms without standardization, significant classification is possible using 100-500 msec waveform data. This result suggests that classification is impossible when using raw data from before the decision response (around 500 msec).

In comparing results for Oz and Fz, the highest rates for the duration coincide with 100-400 msec for the "STD-REG" condition. For other conditions, the higher rate durations of Fz occur later than for the results of Oz. According to the results of the cross validation rate calculations, some delay in the duration for the highest rates is expected. It is impossible to explain the differences across processing conditions for Fz using classification accuracy.

To obtain high classification performance, the features of waveforms should be similar between the training and test data sets. In this paper, the first 20 trials were assigned to the training data set, but the consistency for features of EEG waveforms in the two data sets was not determined. Also, the preparation procedure for the training data set should be taken into consideration.

To help user's visual perception activity or to improve viewing conditions, new procedures for estimating occlusion therapy, observed by users are proposed, using single channel and single-trial EEG waveforms from the frontal (Fz) and occipital areas (Oz) of human brain. To improve estimation performance, a prediction technique was applied to observed EEG waveforms using Support Vector Regression (SVR) in order to formulate the relationship between single-trial EEG and ERP waveforms. Two processing procedures using the regression relationship were proposed. The first 20 trials for each group of Neal stimulus were assigned to a training data set, and the remaining trials were assigned to a test data set. The estimation performance for the test data sets, such as cross validation rates and classification performance using features of the training data set, were compared between the three signal preparation conditions, and across perceptual processes from 150 to 800 msec.

As a result, the performance of cross validation rates of the test data set increased during the perceptual process for both Fz and Oz when predicted waveforms using the regression relationship between single-trial EEG and ERP waveforms were used. Also, the effectiveness of the prediction using the regression relationship for classification performance of occlusion therapy was determined during the perceptual process.
This suggests, that the procedure using the relationship between EEG and ERP is effective, and it is possible to conduct single-trial classifications of checker board pattern viewed by subjects using EEG waveforms. Two signal processing procedures are proposed: REG for real time processing and STD-REG for post procedural processing. According to the relationship between the cross-validation rate and the classification accuracy, the REG procedure is the better one of the two for effective classification of occlusion therapy.

References

Abe, H., Nakayama, M. 2006a. Event-related potential study of Kanji perception process, *J. Inst. Image Informat. Telev. Eng.*, 60: 397–404.

Abe, H., Nakayama, M. 2006b. An investigation into Kanji character discrimination process from EEG signals. *Enformatika, Transact. Eng. Comput. Technol.*, 18: 13–18.

Chang, C.-C., Lin, C.-J. 2001. LIBSVM: a library for support vector machines, 2001. Software available at URL: http://www.csie.ntu.edu.tw/~cjlin/libsvm. (Access date 29 July 2009)

Collobert, R. SVMTorch II. Software available at URL: http://www.idiap.ch/. (Access date 16 January 2008)

Collobert, R., Bengio, S. 2001. SVMTorch: Support vector machines for large-scale regression problems. J. *Machine Learn. Res.*, 1: 143–160.

Posner, M.I., Raichle, M.E. 1994. Images of mind. Scientific American Library, US.

Shiba, Y., Watabe, H. 1976. Toukeiteki Houhou II (Stastistical Method II). Shinyosha, Japan.