

Online Vigilance Analysis Based on Electrooculography

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Abstract—This study provides a highly efficient online method for vigilance analysis and verifies this theory in some experiments. Compared with electroencephalogram (EEG) signals, electrooculography (EOG) signals are easier to collect and faster to process. Some research has proven relations between vigilance and EOG features like blink features and slow eye movement (SEM). This study uses 48 kind of features of eye blinks, SEM and rapid eye movement (REM) from horizontal and vertical channels of EOG signals. It is verified by experiments that the precision of this method is higher than other methods which uses single kind of features like eye blinks. This study also implements an online vigilance analysis method and its precision is close to the offline method after about one minute from the beginning of collecting signals. With the application of dry electrode amplifiers, this algorithm is useful in real-time vigilance estimation in practical environment. This method can be an important part of brain-machine interfaces.

Keywords—online analysis, vigilance, electrooculography.

I. INTRODUCTION

Vigilance refers to the sensitivity that someone maintain when focusing on executing a task. People in many kind of jobs—especially drivers, soldiers and operators of hazardous equipment—need to keep high vigilance over a continuous period of time. A lot of serious accidents are caused by driver fatigue. Therefore, an accurate, fast and online method for vigilance analysis is useful.

In recent years, there have been some studies of collecting and processing electrooculography (EOG) signals. EOG signals contains only two channels, a horizontal channel and a vertical channel, and there are fewer artifacts in EOG signals than in EEG signals. Therefore, EOG signals are easy to analyze and we can design a fast online algorithm to process them. There are some methods for extracting eye blinks, slow eye movement (SEM) and rapid eye movement (REM) and they have a high accuracy only in processing clean EOG signals [1], [2], [3], [4]. However, these methods have poor performance in processing EOG signals collected by some common equipment due to the interference in signals, just like artifacts and voltage drift.

For vigilance analysis, there are some studies on the relations between EOG features and vigilance. Blink duration is used as a feature to estimate sleepiness level and this property

is verified by experiments of simulated driving performance [5], [6], [7], [8]. Another important feature for vigilance estimation is slow eye movement (SEM) [3], [9]. SEM features extracted from EOG signals using discrete wavelet transformation (DWT) are strongly correlated with vigilance [4].

In this research, we introduce several new methods and take advantage of the existing methods [10]. One new method is to normalize the signal amplitude. The source signal collected from the equipment of EOG does not have an equivalent amplitude when used for extracting eye information. Because the resistance of the person and the equipment, especially the epidermis on the face, is not fixed and can be several times larger at one time than another. As a result, if a fixed threshold is used to get some actions of eyes, like eye blinks and eye movements, a lot of errors will be made. In this study we use the average eye blink amplitude as a standard to normalize the amplitude of the source signals in case of an amplitude difference. When this method is used in the online algorithm, the signal can be processed correctly needing data of only about one minute.

Some other methods are used to sense the actions of eyes accurately. Thanks to these, eye blinks, SEMs and REMs can be extracted completely although the artifacts in source signals have a large amplitude and are distributed across almost all the frequency bands. After the actions of the eyes are obtained, 48 kinds of features are extracted from these actions and they can estimate the vigilance of one person by the method of machine learning. This method of using all kinds of EOG features has not yet been used and it works well.

In this study, according to the error rate signal, we use SVM regression to get the predicted vigilance and compare it with the original error rate. It is proved that this algorithm works well on vigilance estimation. In a lot of previous studies of vigilance estimation using methods of machine learning before, vigilance estimation is regarded as a problem of classification and the intermediate state is ignored. Another problem is that EOG signals are dependent on time sequence and the sequence of the signal of a period less than one minute cannot be broken down. This study resolves these problems successfully and finds the relationship between EOG signals and vigilance.

This study contributes to the development part of brain-

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machine interfaces. EOG signals have several advantages over EEG signals; they are easier to collect based on the dry electrode amplifier and the technology of extracting EOG signals from electrical signals on the forehead [11]. EOG signals have a larger amplitude than electromyogram (EMG) or EEG, so noise and artifacts caused by electromagnetic interference are less of a problem. As a result, there are fewer steps in processing EOG signals. The application of this algorithm has an extensive future.

II. METHOD

A. Experiments

EOG signals are recorded by the NeuroScan system. A session is about 67 minutes. 5 sessions from 4 men and 1 woman aged around 20 years old are recorded. One should get up in the morning and have enough sleep last night. Experiments are held after lunch in order that the subject is awake in the beginning but sleepy after about half an hour in the experiment.

The subject looks at the monitor and accomplishes a given target action. There is no noise and the light is soft in the room. Pictures of four colors which are red, yellow, blue and green, appear in the monitor about every 6 seconds and every picture lasts 0.3 seconds. There are 170 kinds of pictures including almost all the traffic signals on the streets. The screen plays all black in the intervals. The equipment that gets the actions of subjects is a box with four buttons of the four colors on it. When a picture is shown on the screen, the subject should press the button with the color of the picture. The function of playing pictures and recording the actions of subjects is brought by the NeuroScan Stim software.

In our experiments, a total of signals of 62 EEG channels and 2 EOG channels are recorded. Four electrodes are placed to the left and right and above and below of the eyes of the subject. The signal of horizontal channel is the electric potential difference of the left and right ones and the signal of vertical channel is from the up and the down ones. The signals are recorded using a 32-bit resolution and 500Hz sampling rate. In order to process the signal faster, the signal is down-sampled at 125Hz. The vigilance data is taken from the error rate data of subjects. The local error rate series calculated by a 2-minute time window were used as the vigilance index (with a step of 8.096s, which is consistent with EOG features).

B. Blink features

The method of getting the difference of the signal and marking the difference signal with a threshold is used as the foundation of an eye blink algorithm [1]. There are several disadvantages of this algorithm. The time of every blink is too short. The voltage drift has a large influence on the process of demarcating blinks using a stable threshold. Some adjacent blinks should be one blink practically. Slow blinks are another kind of blink and these should also be extracted.

In order to solve these problems, we add some advantages in the algorithm. The time of every blink is extended so that its blink time will be close to the real time of the blink. The

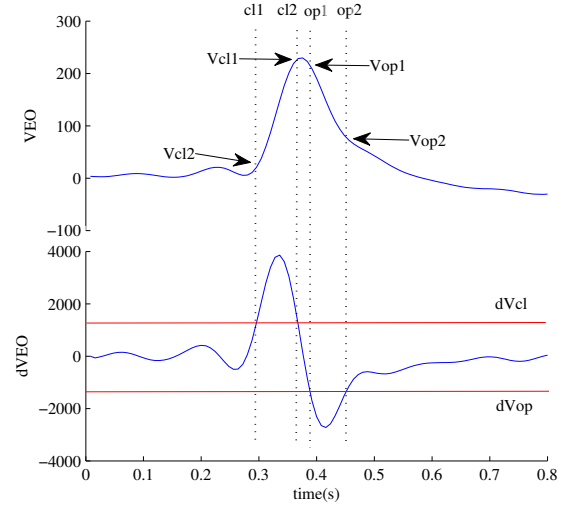


Fig. 1. Example of marking a blink of four points using two thresholds.

threshold is not used to check the voltage to decide whether a waveform is a blink but to check the average voltage of the opening and closing periods. Some blink processes are merged if they should be merged. Finally, an additional method is used to add the slow blinks.

The blink detection algorithm is as follows.

1) *Low-pass filtering*: The vertical EOG signal is filtered by a low-pass filter with a frequency 10Hz using eeglab [12].

2) *Difference of signal*: Get the difference of the signal and every point means the change rate of the EOG signal at the same time. The difference of a signal is as follows, D is the difference signal, V is the signal and R is the sampling rate.

$$D[i] = (V[i + 1] - V[i]) \times R \quad (1)$$

3) *Mark blinks*: At first, use threshold $V_{cl} > 0$ and $V_{op} < 0$ to mark the signal and every point with a value dV_{cl} or dV_{op} will be marked. If there are four continuous marked points with values dV_{cl} , dV_{cl} , dV_{op} and dV_{op} , these four marks will be recorded. There is an example shown in Fig.1.

Then for every four marked points $cl1$, $cl2$, $op1$ and $op2$, we calculate the voltage for the blink as follows.

$$V = ((V_{cl2} - V_{cl1}) + (V_{op1} - V_{op2}))/2 \quad (2)$$

If a group of marked points has $V > V_{min}$, it is judged as a possible blink and recorded.

In order to mark the slow blinks, we pick the left marked points. For every $op1$ and $op2$, we try to use a smaller threshold V_{cls} to mark two points before $op1$. If the time interval between the wave peak and the wave valley is larger than a threshold T_{min} , it is judged as a slow blink.

4) *Extend blink time*: After all the blinks are picked, we extend the time of every blink. We use two thresholds V_{clth} and V_{opth} to extend the wave peak and wave valley respectively. After this process, every blink is marked at four time points $clth1$, $clth2$, $opth1$ and $opth2$.

5) *Merge blinks*: We check every group of adjacent blinks for whether they should be merged. If the time interval between two adjacent blinks is less than T_{int} and one of the

two blinks has blink time less than T_{short} , these two blinks should be merged and treated as one blink.

6) *Get features*: Finally, features of eye blink from EOG will be extracted. The feature of one blink will be calculated as follows, T is the time point, V is the signal, D is the difference of signal, S is the velocity and E is the energy. For every blink, T_{blink} is the total eye-blink time, T_{close} is the time of closing eyes, T_{open} is the time of opening eyes, T_{closed} is the time when the eyes are closed, $perclos$ is the ratio between T_{closed} and T_{blink} , T_{int} is the time interval between two blinks, S_{close} is the average speed of closing eyes, S_{open} is the average speed of opening eyes, $S_{closemax}$ is the maximum speed of closing eyes, $S_{openmax}$ is the maximum speed of opening eyes and E_{blink} is the total eye-blink energy.

$$T_{blink} = T_{opth2} - T_{clth1} \quad (3)$$

$$T_{close} = T_{clth2} - T_{clth1} \quad (4)$$

$$T_{open} = T_{opth2} - T_{opth1} \quad (5)$$

$$T_{closed} = T_{opth2} - T_{clth2} \quad (6)$$

$$perclos = T_{closed}/T_{blink} \quad (7)$$

$$T_{int}[i] = T_{clth1}[i] - T_{opth2}[i - 1] \quad (8)$$

$$S_{close} = \left(\sum_{i=T_{clth1}}^{T_{clth2}} D_i \right) / T_{close} \quad (9)$$

$$S_{open} = \left(\sum_{i=T_{opth1}}^{T_{opth2}} D_i \right) / T_{open} \quad (10)$$

$$S_{closemax} = \max_{T_{clth1} \leq i \leq T_{clth2}} D_i \quad (11)$$

$$S_{openmax} = \max_{T_{opth1} \leq i \leq T_{opth2}} D_i \quad (12)$$

$$E_{blink} = \sum_{i=T_{clth1}}^{T_{opth2}} V_i^2 \quad (13)$$

After the feature of every blink is picked, we calculate the features for 8-second intervals. The first dimension is the number of blinks in 8 seconds. The left dimensions are the average, maximum and minimum values of 11 features calculated just now of all blinks in 8 seconds.

C. Normalization

Because the resistance of the total circuit of the signal connection and amplifier is not fixed, the amplitude of the signal has a large variance. Because of this problem, the source EOG signal should be normalized and then its amplitude will be an almost fixed value.

In experience, the average blink amplitude is a good standard because its value has a small variance no matter which state one has and this theory is verified by a lot of EOG signals. Based on this theory, a normalization algorithm is used to normalize the amplitude of EOG signals. This algorithm uses an iterative method. If a small threshold is given to judge

whether a waveform is a blink, some other waveforms such as REMs or SEMs will be picked up because their amplitudes are small in vertical EOG signals. As a result, the amplitude of all the blinks marked using this small threshold will be less than the practical one. When a standard amplitude is used to normalize this value, the signal will be amplified. On the other hand, if a large threshold is used, the signal will be amplified with a multiplier less than 1. After several iterations, the amplitude of signal will be normalized to a given standard.

The normalizing algorithm is as follows.

1) *Preprocess*: Same as extracting blink features, we get the filtered signal using a low-pass filter with frequency 10Hz and record this signal. The first scale factor is a fixed value divided by the average value of this signal getting rid of typical values.

2) *Adjust signal amplitude*: We use the multiplier to adjust the amplitude of the signal as follows and m is the multiplier.

$$V_{new}[i] = V_{old}[i] \times m \quad (14)$$

3) *Get blink features*: For the new signal, we use the blink algorithm to extract all the blinks and calculate the average amplitude of blinks V_{blink} . Then we get the multiplier m using the standard as follows.

$$m = V_{normal}/V_{blink} \quad (15)$$

If the iteration of the signal is in a stable state, for example, a fixed value or two alternating fixed values, the iteration process is completed. If the process is not completed, return to process 2.

4) *Get normalized signals*: After this iteration, we get a multiplier. The normalized EOG signals are adjusted using this multiplier. For simplicity, the two channels of EOG are adjusted together using the multiplier. These normalized signals are the final signals for all the feature extracting processes.

D. SEM features

The SEM feature is a good feature for vigilance estimation because its performance has an important relation with the fatigue and drowsiness of people. In order to get SEMs more accurately, two methods of Fourier transformation and wavelet transformation are used. The resulting of feature is the number of SEMs in 8 seconds and it has 2 dimensions because of the two methods.

In the Fourier transformation method, we use a band-pass filter with frequency 0.5Hz and 2Hz to process the horizontal EOG signal. The filtered signal is measured by a threshold and a sequence of a wave peak and a wave valley is considered as a SEM. The number of SEMs in 8 seconds is one of the SEM features.

The Fourier transformation can make the frequency features of the signal stand out and the wavelet transformation can show the eye movements clearly. A wavelet decomposition operates on the horizontal EOG channel of signals and the Daubechies order 4 wavelet (db4) is selected because the shape of this wavelet is the most similar to eye movements.

The sampling rate is 125Hz and the period is 8 seconds. Because there are 1000 points in one period, we use 1024 points (24 points from the last period) to extract a feature point and divide the signal using a 10-order wavelet transformation. The 6 and 7 scale is selected to express SEMs. After the 6 and 7 scale of coefficients are reconstructed to a signal, we use a threshold to detect SEMs just like using a Fourier transformation.

E. REM features

Like SEM features, rapid eye movement (REM) features also have relationship to vigilance. REM is another kind of eye movement and number of REMs, time of REMs and energy of REMs are correlated with drowsiness. The feature defined as number of REMs is extracted by the difference of signal and the feature defined as time of REMs is extracted by two methods, Fourier transformation and wavelet transformation.

This is the Fourier transformation method. First, use a band-pass filter with frequency between 3Hz and 11Hz to process the signal. Then get the difference of the signal. Finally, we use a threshold to get how long there is in REM action every 8 seconds.

The other two methods are the same as the process of getting SEM features. The frequency of the band-pass filter is between 2.5Hz and 7Hz. The scale of coefficients of wavelet reconstructing is scale 4, 5 and 6.

F. Energy features

Just like the method of EEG analysis, the energy of different frequency bands in the EOG can express the intensity of different kinds of eye movements. We use two methods to get the energy features from the EOG, Fourier transformation and wavelet transformation.

For the Fourier transformation, five bands are selected as features. The SEM band is between 0.1Hz and 1.8Hz. The REM bands are 1.8Hz-3Hz, 3Hz-6Hz, 6Hz-9Hz and 9Hz-11Hz. According to the Parseval equation, the sum of squares in the time domain equals to that in the frequency domain. Therefore, the energy of a band is the sum of squares of signal values after band-pass filtering; this is calculated every 8 seconds.

$$E_{8s} = \sum_{i=1}^{125 \times 8} V_i^2 \quad (16)$$

Using wavelet transformation, we get the SEM energy in scale 5 and 6 and the REM energy in scale 3 and 4. The energy is also calculated in the time domain. We add the last 24 points of the last period so that there are 1024 points for us to process. After the wavelet transformation, the last 1000 points are selected.

Although the energy of a frequency band or wavelet band can express the intensity of eye movements well, the ratio of energy of two different bands is more important for vigilance estimation. When a person is excited, high frequency eye movements will increase and low frequency eye movements will decrease. When a person is drowsy, vice versa. As a result,

a feature of ratio between energy of low frequency and energy of high frequency is used.

The ratio of energy for frequency bands is between 0.1Hz-0.8Hz and 0.8Hz-11Hz and that for wavelet bands is between scale from 4 to 6 and scale from 4 to 10. The ratios are calculated as follows.

$$R_{8s} = \left(\sum_{i=1}^{125 \times 8} V_{1i}^2 \right) / \left(\sum_{j=1}^{125 \times 8} V_{2j}^2 \right) \quad (17)$$

G. Feature processing

There are 48 features extracted from the 2-channel EOG signals. Since the features have a lot of noise and are not smooth enough, we use the linear dynamical system (LDS) [13] to process features. Its effect is better than simple methods like moving average smoothing. LDS is an unsupervised learning method and it can increase the main component and reduce others. Because the main component of these features is vigilance, a feature processed by LDS has a higher correlation with vigilance.

Another step of feature processing is to adjust features to a scale of 0 and 1. In this step, two thresholds are used for each feature to avoid extreme values so that noise is reduced. After feature processing, it is easy to observe the relationship between features, the error rate.

H. Regression using machine learning methods

After all the features are prepared, a machine learning method is used to analyze the relations between features and vigilance. First, use principle component analysis (PCA) to process higher-dimension features. Then divide the data for each subject into two parts, a training set and a testing set. The result of relation coefficients and testing precision proves that EOG signals can estimate vigilance and this method is a good way to implement this algorithm.

We use SVM regression to train the model from features and error rate and then predict values of vigilance. The result is compared with error rate. Data for each subject is processed separately because a model trained by data of one subject cannot work well on data of another. The data for each subject is divided into two parts of training set and testing set and then cross validation is done.

SVM with RBF kernel works well. There are three parameters in SVM needed to be tuned. Every parameter is selected from a set of 21 values from 2^{-10} to 2^{10} . All of the 9261 values of parameters are searched and the final parameter is determined. A good parameter can not only predict values accurately but also balance the mean squared error and squared correlation coefficient well. After all, it is important to make the model stable in this application of EOG.

III. RESULT

A. Eye actions detection

1) *Eye blinks detection*: In the eye blink detection algorithm, several advantages are brought. More kinds of eye blink are detected, such as long-time blinks and slow blinks. Time of

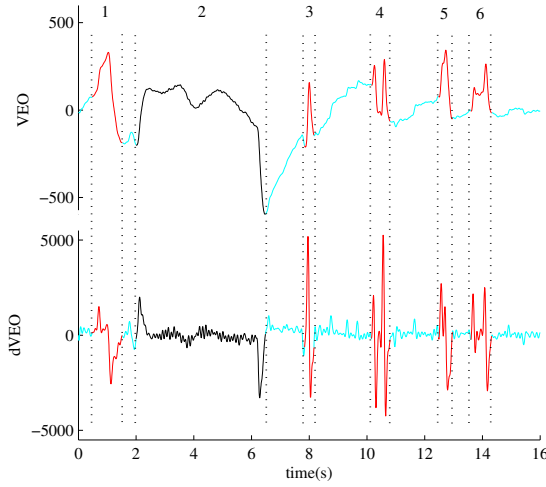


Fig. 2. Example of eye blinks detection.

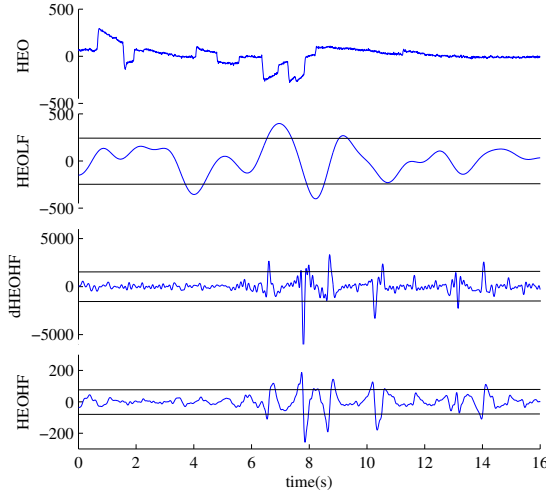


Fig. 3. Example of eye movements detection using Fourier transform.

blinks is estimated more accurately. These advantages improve the accuracy of blink features.

A result of eye blink detection is showed in Fig.2. VEO is the source vertical EOG signal filtered by a low-pass filter with frequency 10Hz and dVEO is the difference of the filtered source signal. There are 6 eye actions in a period of 16 seconds. Using this improved algorithm, the type of every action is distinguished completely. No.1 is a slow blink, No.2 is an eye movement but not a blink, No.3 and No.5 are common blinks, No.4 has two blinks in it and No.6 has only one blink because the two blinks in it are merged. It is proved that kinds of blinks are detected all and few blinks are detected incorrectly.

2) *Eye movements detection*: A result of eye movements detection is showed in Fig.3 and Fig.4. This signal is selected with the same subject and the same period of Fig.2 of eye blink detection.

Fig.3 shows the result of the band-pass filter. HEO is the source horizontal EOG signal. HEOLF is the low-frequency part including SEMs. We can count SEMs every 8 seconds

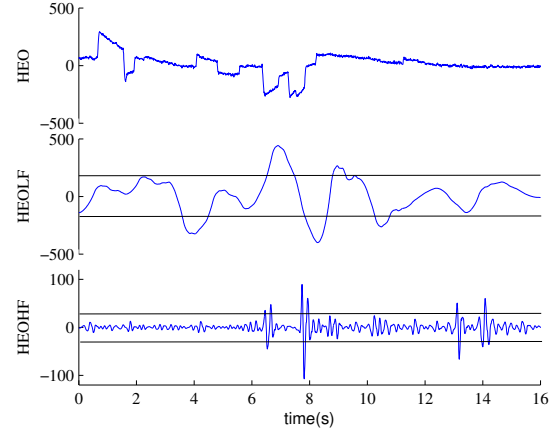


Fig. 4. Example of eye movements detection using wavelet transform.

TABLE IV
CORRELATION COEFFICIENTS BETWEEN ERROR RATE AND PRINCIPLE COMPONENT OF FEATURES.

| Subject | 1st | 2nd | 3rd |
|---------|--------|--------|--------|
| 1 | -0.766 | -0.201 | 0.244 |
| 2 | -0.868 | 0.190 | 0.148 |
| 3 | -0.844 | 0.305 | -0.148 |
| 4 | -0.853 | -0.098 | 0.101 |
| 5 | -0.726 | 0.379 | 0.287 |
| Average | -0.811 | 0.115 | 0.126 |

using a threshold to process this signal. HEOHF is the high-frequency part and dHEOHF is the difference of HEOHF. dHEOHF shows the velocity of eye movements and eyes are in REM state during periods when it is more than a threshold. Therefore, we get how long there is REM action every 8 seconds. HEOHF is used the same as HEOLF to count REMs.

Fig.4 shows the result of the wavelet filter. HEO, HEOLF and HEOHF are also the source horizontal EOG signal, its low-frequency and its high-frequency part. We consider that signal brought from wavelet filter is similar to that from band-pass filter but a little more correct.

B. Correlations between features and vigilance

There are 48 features extracted by EOG signals including 34 features of eye blink, 2 features of SEM, 3 features of REM and 9 features of energy. From the result in Table.I, II, III, we can see that almost all features including blink, SEM, REM and energy features correlate with error rate. Therefore, these features will be used for vigilance estimation.

From these tables, it is also clear that simple features such as number of blinks, number of SEMs, number of REMs and REM time, are more useful. They have larger correlation coefficients with vigilance and they are almost enough. However, a lot of other features in addition are provided to decide whether they include some component that common features don't include. PCA is used to extract components from these features and to process features for classification.

Table.IV shows correlation coefficients of the first three

TABLE I
CORRELATION COEFFICIENTS BETWEEN ERROR RATE AND COMMON EOG FEATURES.

| Subject | blinks | SEMs_Fourier | SEMs_wavelet | REMtime | REMs_Fourier | REMs_wavelet |
|---------|--------|--------------|--------------|---------|--------------|--------------|
| 1 | -0.790 | 0.655 | 0.641 | -0.796 | -0.734 | -0.704 |
| 2 | -0.705 | 0.606 | 0.669 | -0.796 | -0.811 | -0.844 |
| 3 | -0.864 | 0.712 | 0.606 | -0.702 | -0.806 | -0.752 |
| 4 | -0.822 | 0.762 | 0.676 | -0.866 | -0.856 | -0.802 |
| 5 | -0.797 | 0.799 | 0.679 | -0.777 | -0.797 | -0.749 |
| Average | -0.796 | 0.707 | 0.654 | -0.788 | -0.801 | -0.770 |

TABLE II
CORRELATION COEFFICIENTS BETWEEN ERROR RATE AND EYE BLINK FEATURES.

| Subject | T_{blink} | T_{close} | T_{open} | T_{closed} | $perclos$ | T_{int} | S_{close} | S_{open} | S_{maxcl} | S_{maxop} | E_{blink} |
|---------|-------------|-------------|------------|--------------|-----------|-----------|-------------|------------|-------------|-------------|-------------|
| 1 | 0.651 | 0.724 | 0.576 | 0.648 | 0.750 | 0.690 | -0.813 | -0.708 | -0.819 | -0.669 | 0.442 |
| | 0.620 | 0.677 | 0.179 | 0.633 | 0.731 | 0.569 | -0.813 | -0.665 | -0.826 | -0.733 | 0.009 |
| | 0.693 | 0.698 | 0.769 | 0.663 | 0.724 | 0.718 | -0.811 | -0.771 | -0.838 | -0.809 | 0.725 |
| 2 | 0.821 | 0.840 | 0.551 | 0.792 | 0.637 | 0.785 | -0.676 | -0.755 | -0.635 | -0.731 | 0.821 |
| | 0.811 | 0.874 | 0.086 | 0.796 | 0.724 | 0.566 | -0.815 | -0.687 | -0.658 | -0.588 | 0.877 |
| | 0.815 | 0.861 | 0.747 | 0.769 | 0.675 | 0.801 | -0.626 | -0.824 | -0.434 | -0.844 | 0.809 |
| 3 | 0.677 | 0.780 | 0.729 | 0.643 | 0.724 | 0.844 | -0.893 | -0.776 | -0.896 | -0.640 | 0.620 |
| | 0.628 | 0.585 | -0.223 | 0.614 | 0.538 | 0.843 | -0.813 | -0.818 | -0.893 | -0.873 | 0.446 |
| | 0.694 | 0.838 | 0.885 | 0.635 | 0.737 | 0.844 | -0.750 | -0.538 | -0.682 | 0.168 | 0.728 |
| 4 | 0.717 | 0.333 | 0.682 | 0.715 | 0.612 | 0.720 | -0.711 | -0.632 | -0.689 | -0.446 | 0.395 |
| | 0.642 | 0.346 | -0.190 | 0.659 | -0.141 | 0.715 | -0.724 | -0.525 | -0.830 | -0.710 | 0.488 |
| | 0.748 | 0.665 | 0.858 | 0.727 | 0.699 | 0.726 | -0.169 | -0.037 | -0.227 | 0.108 | 0.675 |
| 5 | 0.689 | 0.258 | 0.732 | 0.693 | 0.714 | 0.688 | -0.707 | -0.734 | -0.735 | -0.662 | 0.461 |
| | 0.706 | 0.715 | -0.371 | 0.690 | 0.532 | 0.671 | -0.644 | -0.706 | -0.766 | -0.696 | 0.731 |
| | 0.652 | 0.400 | 0.666 | 0.678 | 0.772 | 0.709 | -0.484 | -0.667 | -0.508 | -0.736 | 0.635 |
| Average | 0.711 | 0.587 | 0.654 | 0.698 | 0.687 | 0.745 | -0.760 | -0.721 | -0.755 | -0.630 | 0.548 |
| | 0.681 | 0.640 | -0.104 | 0.678 | 0.477 | 0.673 | -0.762 | -0.680 | -0.795 | -0.720 | 0.510 |
| | 0.720 | 0.693 | 0.785 | 0.694 | 0.721 | 0.759 | -0.568 | -0.567 | -0.538 | -0.423 | 0.714 |

TABLE III
CORRELATION COEFFICIENTS BETWEEN ERROR RATE AND ENERGY FEATURES.

| Subject | 0.1-1.8Hz | 1.8-3Hz | 3-6Hz | 6-9Hz | 9-11Hz | 6-7scale | 3-4scale | ratio_freq | ratio_wavelet |
|---------|-----------|---------|--------|--------|--------|----------|----------|------------|---------------|
| 1 | 0.685 | -0.679 | -0.679 | -0.711 | -0.802 | 0.619 | -0.667 | 0.513 | -0.760 |
| 2 | 0.625 | -0.657 | -0.778 | -0.744 | -0.748 | 0.650 | -0.808 | 0.815 | -0.633 |
| 3 | 0.619 | -0.716 | -0.774 | -0.525 | -0.501 | 0.813 | -0.639 | 0.564 | -0.884 |
| 4 | 0.705 | -0.843 | -0.805 | -0.745 | -0.811 | 0.842 | -0.791 | 0.445 | -0.586 |
| 5 | 0.795 | -0.788 | -0.693 | -0.755 | -0.809 | 0.625 | -0.716 | 0.781 | -0.754 |
| Average | 0.686 | -0.737 | -0.746 | -0.696 | -0.734 | 0.710 | -0.724 | 0.623 | -0.723 |

TABLE V
RESULT OF REGRESSION TEST.

| Subject | Mean squared error | Squared correlation coefficient |
|---------|--------------------|---------------------------------|
| 1 | 0.00738624 | 0.909072 |
| 2 | 0.00708072 | 0.831733 |
| 3 | 0.00529245 | 0.913794 |
| 4 | 0.00936741 | 0.914622 |
| 5 | 0.00427124 | 0.936210 |
| Average | 0.00667961 | 0.901086 |

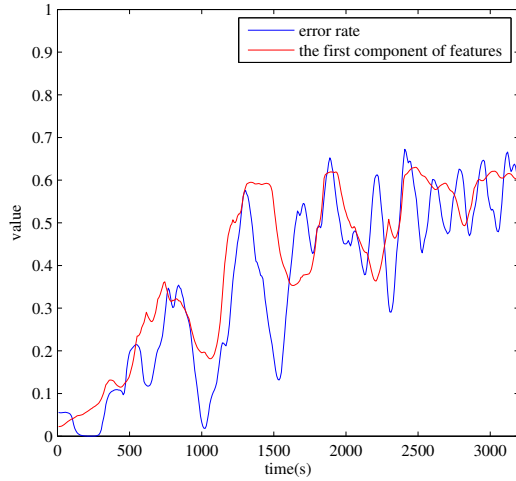


Fig. 5. Example of comparison between error rate and the first component of features.

principle components. Only the first principle component is stably correlated with the target label; the others are not stable. This brings up an important fact that the first principle component of all features is closely related to error rate, or vigilance. Fig.5 shows the error rate in blue and the first component in red for subject No.2. Therefore, we completely fetch features from EOG signals and process them and a regression test will be brought soon.

C. Predicted result of regression

The result of the regression test is in Table.V.

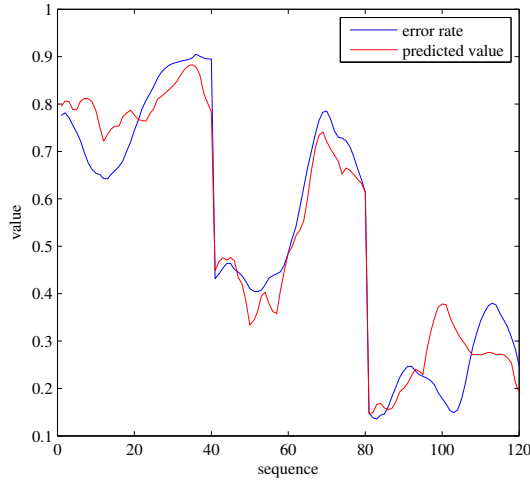


Fig. 6. Example of comparison between error rate and predicted result.

Data for each subject is 400 points long. It is divided into 10 parts with the same length. In most previous EOG research, the sequence of points is changed. However, the EOG signal is time-sequential and cannot divide into parts with a short term. For this reason, all 400 points are divided sequentially. After the data is divided, the 2nd, 5th and 8th part are selected as the testing set and others are selected as the training set.

We use LibSVM [14] to train and test data. After a process of parameter selection, all of the parameters are selected.

- $s=3$ (ϵ -SVR)
- $t=2$ (RBF kernel)
- $c=8$
- $g=1/64$
- $p=1/1024$

From the result we see that this test gives good accuracy. Fig.6 shows the best predicted result in red compared with the original label of error rate in blue, or vigilance. In the application of a fatigue detecting system, we only need to know whether the subject is fatigued enough and this algorithm will work better.

D. Speed of algorithm

This algorithm is fast enough. On a 3.2GHz Core i5 with 4GB memory, the program in Matlab takes less than 8 seconds to process signals for 3200 seconds signals. If it is used to output the vigilance of one person every 8 seconds, this algorithm can be used online.

IV. CONCLUSION

This work is based on some existing work on EOG signal processing and relations between EOG and vigilance. In this work, an algorithm to extract all EOG features including blinks, SEMs, REMs and energy is put forward. All features, especially blink features, are detected and analyzed more accurately. The results from experiments show that the algorithm gives high precision and is fast enough for online use. In the future, more experiments will be done and the stability and robustness of this algorithm will be improved. This study provides an important result in brain-machine interfaces. This

work will be widely used in vehicles, army and hospitals with simple and portable equipment of EOG collection.

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