Online Vigilance Analysis Combining Video and Electrooculography Features

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Abstract. It is widely acknowledged that one can never emphasize vigilance too much, especially for drivers, policemen and soldiers. Unfortunately, almost every existing vigilance analysis system has its limitations and suffers from poor illumination, horizon of the cameras, together with various appearance and behaviors of the subjects. In this paper, we propose a novel system to analysis vigilance level combining both video and Electrooculography (EOG) features. Our system exploits 16 kinds of features extracted from an infrared camera and 48 kinds of features from horizontal and vertical channels of EOG signals. For one thing, the video features include percentage of closure (PERCLOS), eye blinks, slow eye movement (SEM), rapid eye movement (REM), which are also extracted from EOG signals. For another, other features like yawn frequency, body posture and face orientation are extracted from the video based on Active Shape Model (ASM). The results of our experiments indicate that our approach outperforms that based on either video or EOG merely. In addition, the prediction offered by our model is in close proximity to the actual error rate of the subject. We firmly believe that this method can be widely applied to prevent accidents like fatigued driving in the future.

Key words: Vigilance Analysis, Fatigue Detection, Active Shape Model, Electrooculography, Support Vector Machine, Feature Extraction, Linear Dynamic System

1 Introduction

There is no doubt that vigilance plays a crucial role in our daily life. As the technology advances throughout the world, the speed of transportation means such as vehicles, high-speed trains, subways and planes are growing faster and faster. Consequently, it is more and more essential to ensure the vigilance level of the drivers since a large number of accidents are resulted from fatigued driving, which has been investigated by [1] and [2]. Meanwhile, vigilance is an indispensable characteristic for other occupations such as policemen, soldiers and operators who have to deal with hazardous equipments. Thus, an efficient and accurate system is badly in need in order to prevent accidents by warning the users in advance.

In the last two decades, extensive researches have been conducted regarding vigilance analysis, which can be found in [3]. These studies can be broadly classified into 3 categories based on the techniques which are adopted during the procedure of feature extraction: (infrared) video, electrooculography (EOG) and electroencephalography (EEG).

Firstly, vigilance analysis based on video is the most convenient one among the three approaches. For one thing, compared with EOG and EEG based systems, in which the subjects have to interact directly with the equipments, cameras are much less intrusive. For another, not only eye movement can be measured through video, but yawn state and facial orientation can be estimated [4][5][6]. Features such as movement of eyelid, gaze point and head, facial expressions, percentage of closure (PERCLOS), have been used in former systems [7]. Unfortunately, there are three apparent drawbacks for video approach: the accuracy would decrease due to various luminance; the range of the video is limited to the horizon of the cameras; the recognition usually fails on account of the appearance of the subjects such as wearing sunglasses.

Secondly, vigilance analysis based on EOG signals is a moderate method among the three. Compared with video signals, this approach is irrelevant to the environment. Compared with EEG signals, EOG signals are easier to analyze since only four channels (two horizontal channels and two vertical channels) are included. Some studies have been conducted on the relationship between EOG features and vigilance. In order to estimate the vigilance level, features like eye blinks, blink duration, slow eye movement (SEM), rapid eye movement (REM) are utilized, which has been proved to be accurate according to [8].

Finally, vigilance analysis based on EEG signals gains a good accuracy. It has been shown that both delta waves (0-4 Hz), which are relevant to slow wave sleep (SWS), and theta waves (4-7 Hz), which are relevant to drowsiness of older children and adults play significant roles in vigilance analysis [3]. Nevertheless, it is ineffective as a result of its poor user experience of the interaction.

From our perspective, in order to utilize comprehensive information like yawn state and improve the accuracy of vigilance analysis, we construct an online vigilance analysis system combining both video and EOG features. On one hand, we extract the displacements of feature points around eyes and mouth based on the well-known Active Shape Model (ASM), as well as the location of the eyelids based on a binarization approach. Afterwards, we calculated the average height, area and PERCLOS of eyes and mouth. Finally we extract features of blinks and eye movements for vigilance analysis from the information we have. On the other hand, we preprocess the EOG signals using a low-pass filter with the frequency of 10Hz and a normalization procedure. After that, features of blinks and eye movements are extracted according to the algorithm proposed in [9]. In our experiments, based on the actual error rate signals, we employ SVM regression to offer the prediction of the vigilance level. Compared with the actual error rate, our algorithm is proved to work rather well for the online vigilance estimation. In addition, although the accuracy provided by the video features is not so good as that of EOG features, the combination of both video and EOG features outperform both models running alone.

Overall, the remaining part of the paper is organized as follows. In Section 2, our online vigilance analysis system is introduced in details. In section 3, the preprocess in our system is illustrated. We describe the approaches of features extraction in Section 4. Experiments and analysis are conducted in section 5, followed by the conclusion and further discussions in section 6.

2 Vigilance Analysis System

2.1 Equipments

The experimental environment of our vigilance analysis system is illustrated in Fig. 1

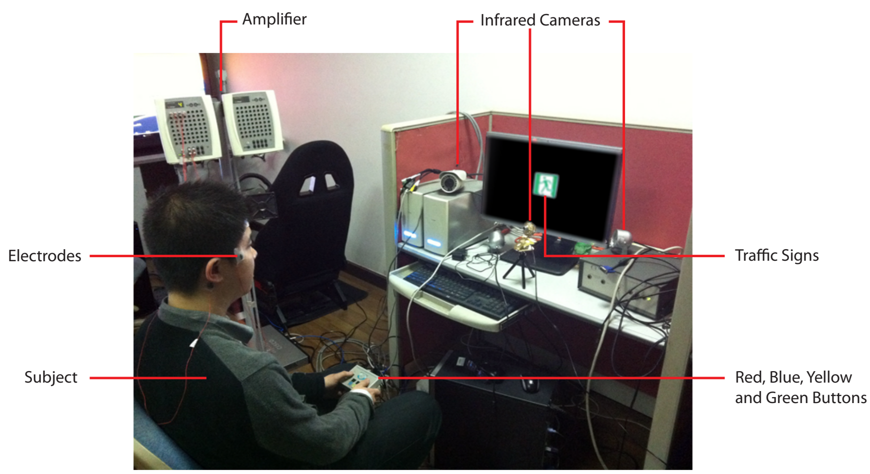


Fig. 1. The actual experimental environment analysis system by combining video and EOG features.

As is shown above, the video signals are extracted from infrared cameras, which are located in front of and aside of the subject. Meanwhile, the EOG signals are extracted by 8 electrodes and recorded by the NeuroScan system (Neuroscan Inc, Herndon, VA, USA). There are 4 electrodes on the forehead, 2 for vertical signals, and 2 for horizontal signals. The monitor screen is located exactly in front of the subject. Different traffic signs in four colors (red, green, blue and yellow) are displayed on the screen every 6 seconds and each sign lasts for only 0.5 seconds. Meanwhile, the subject is ought to press the button with the same color as the signs flashed on the screen. Therefore, not only the actions of the subjects could be recorded but the actual error rate could be calculated. To view the details of our experiments, please refer to Section 4.

2.2 Overall Process

The whole process of our vigilance analysis system is illustrated in Fig. 2. In summary, four procedures including preprocessing, feature extraction, model training and prediction of vigilance are followed for both video and EOG signals.

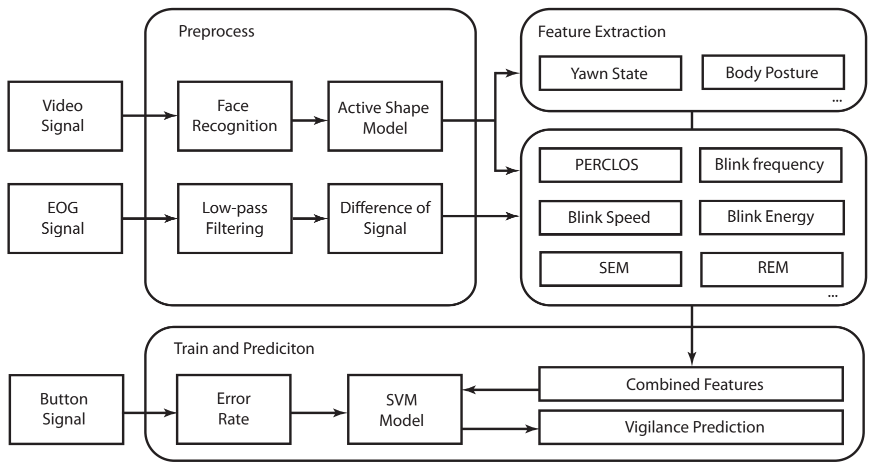


Fig. 2. The proposed vigilance analysis system by combining video and EOG features.

3 Preprocess

As is illustrated in Section 2, video signals are captured by infrared cameras which is in front of the subject. The recorded video has the resolution of 640×480 pixels with 30 frames per second in RGB color. In order to extract features based on video, we need to preprocess the images in each frame. For a single test of 67 minutes, the raw data is approximately 70 GB. For each frame, we apply the famous Active Shape Model [10] for further feature extraction. After acquiring landmarks of eyelids, eyeballs and mouth, we employ an extraction algorithm to get blink, eye movement and yawn information.

3.1 Face Recognition

Firstly, we employ a cascade Adaboost classifier based on Haar-like features, which is proposed by [11] for the face recognition procedure. If multiple faces are successfully recognized in the frame, the one with the largest area is regarded as the subject's face.

3.2 Active Shape Model

After getting the approximate location of the subject in the image, we adopt the Active Shape Model (ASM), which is a statistical model to recognize the shape of deformable object, to get the displacements of both eyes and mouths [10].

Generally speaking, ASM is used to locates landmarks on the image by fitting the parameters of the shape using optimization techniques like gradient descent. The shape S provided by ASM is consisted of n landmarks, explicitly $S = [x_1, y_1, x_2, y_2, ..., x_n, y_n]$, where x_i, y_i are the coordinates of the i_{th} landmark. In our vigilance system, there are totally 68 landmarks for the ASM Model. The distance $D(i, j)$ between landmarks i and j is defined as follows:

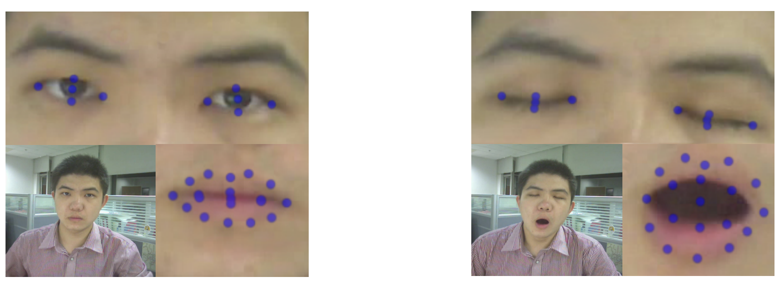
$$D(i,j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

Furthermore, we calculate the current average height of both eyes and that of the mouth according to:

$$H_e = \frac{D(35,33) - D(34,32)}{2}$$

$$H_m = D(64,57)$$

Similarly, the approximate areas A_e, A_m are calculated according to the polynomial shape of the eyes and mouth. Fig. 3(a) indicates landmarks calculated by Active Shape Model when the subject is sober while Fig. 3(b) shows landmarks when the subject is yawning.



(a) Sober State

(b) Fatigued State

Fig. 3. Examples of landmarks on different state of vigilance.

3.3 Low-pass Filtering

The preprocessing of EOG features is much different from that of video signals and EEG signals. Compared with video image, there is no need to extract information of shapes from EOG signals. Compared with 62 channels for EEG, there are only 2 channels in EOG. Firstly, in order to extract blink features, we filter the vertical EOG signal by a low-pass filter with a frequency of 10Hz using EEGLab [12]. Afterwards, a multiplier is used to adjust the amplitude of the signals.

3.4 Difference of Signals

In order to obtain the variance ratio from the EOG signals, we compute the difference of signals for blink feature extraction. Denote D as the difference signal, V as the signal and R as the sampling rate, we have:

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

4 Feature Extraction

In this section, we will briefly introduce how we extract the features based on video and EOG signals. Both kinds of features are extracted based on a time window of 8 seconds from a 67-minutes test.

4.1 Video Features

It is widely acknowledged that the information we have including average height and area of eyes and mouths has interior relationship with the vigilance of subject. Besides, the yawn frequency and the orientation of the face also helps a lot. The video features we extracted are as follows:

- PERCLOS of eyes
  It is widely acknowledged that PERCLOS of eyes, which refers to the percentage of eye closure, is an efficient feature to estimate vigilance. [13] We adopt four PERCLOS features for both eyes. One is calculated as follows:

  $$PERCLOS_e = \frac{\overline{H}_e - H_e}{\overline{H}_e}$$

  where $\overline{H}_{eyes}$ indicates the average open eye height above a certain threshold. Another PERCLOS feature is calculated according to the areas of eyes. Finally, the proportions of fully-closed and half-closed eyes during a certain time window are also regarded as PERCLOS features.

- Blink frequency
  The frequency of blinks also have a strong relationship to vigilance. In order to calculate that, we setup four thresholds H_{c1}, H_{c2}, H_{o1}, H_{o2}, , which indicate the relative height when eyes are about to close, already closed, about to open and fully open. This procedure suggests a complete blink. And 2 half-blink features are counted by H_{c1} and H_{o1}, H_{c2} and H_{o2}

- Eye Movement
  The relative position of the pupil could be estimated by ASM. Thus the moving frequency of eyes are recorded as an important feature. During each time window, we calculate the movement of eye pupils and its the amplitude. The speed of the eye movement is also calculated as a feature.

- PERCLOS of mouth
  It is similar with that of eyes. The only difference is that there are more points to process, which is implied in Fig. 3.

- Yawn frequency
  Since an action of yawn suggest significantly that the subject has already been fatigued. The window size w for yawn state should be large enough such as 16 seconds $\times$ 30 frames. Denote the average of the least k heights of mouth as H_m^k

$$Y_i = \frac{\sum_{j=i-w}^{i}(H_j/H_m^k) > C}{w}$$

  Here C is a threshold and indicates the ratio between open mouth height and normal mouth height when the subject is about to yawn.

- Body Posture
  We estimate the posture of body by locating the relative position of eyes, nose and mouth on the face. Denote orientation of the face as α, θ and β, corresponding to different reference of eyes, nose and mouth. This degree can be calculated as follows:

$$\alpha = \frac{D(67,2)}{D(67,12)}; \theta = \frac{D(31,0)}{D(36,14)}; \beta = \frac{D(66,3)}{D(66,11)}$$

  where points 67, 66, 31, 36 denote the center of the nose, mouth, left and right pupil separately while the others indicate the left and right side of the face horizontally and correspondingly.

4.2 EOG Features

1. Blink Features
   After the preprocess of EOG signals, every blink is marked at four time points $c1, c2, o1$ and $o2$, which indicate the time when the eye is to close, closed, to open and opened. Denote V as the signal, D as the difference of signal, we have the following features:

$$T_{blink} = T_{o2} - T_{c1}; \quad T_{close} = T_{c2} - T_{c1}$$

$$T_{open} = T_{o2} - T_{o1}; \quad T_{closed} = T_{o2} - T_{c2}$$

$$S_{close} = \frac{\sum_{i=T_{c1}}^{T_{c2}} D_i}{T_{close}}; \quad S_{open} = \frac{\sum_{i=T_{o1}}^{T_{o2}} D_i}{T_{open}}; \quad E_{blink} = \sum_{i=T_{c1}}^{T_{o2}} V_i^2$$

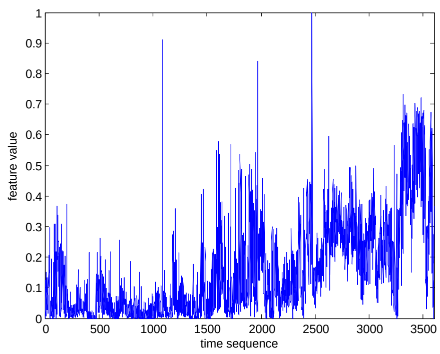
   where T indicates the time during a window size, S indicates the speed, and E indicates the energy of blinks.

2. Eye Movements
   Two kinds of eye movements, Slow Eye Movement (SEM) and Rapid Eye Movement (REM) are extracted, according to different kinds of time threshold in [14]. In

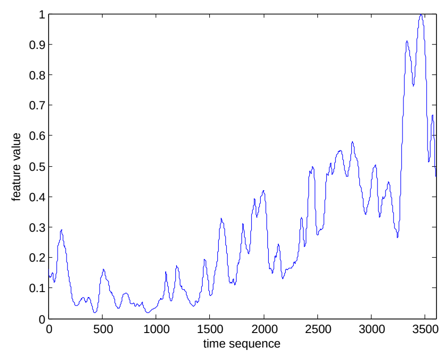
order to get these features more accurately, two methods of Fourier transformation and wavelet transformation are used. In the Fourier transformation method, we use a band-pass filter with frequency 0.5Hz and 2Hz to process the horizontal EOG signal. The sampling rate is 125Hz and the period is 8 seconds.

4.3 Linear Dynamic System

Considering the fact that both video and EOG features introduce much noise, we adopt the linear dynamical system, which is proposed in [15] to process them. As an unsupervised learning method, LDS can increase the main component of the features and reduce the noise, leading to a higher correlation with vigilance. An example is illustrated in Fig. 4, where the noise in the feature is successfully expunged.



(a) Without LDS



(b) With LDS

Fig. 4. Examples of feature extraction using linear dynamic system.

Finally, all the features are normalized between 0 and 1. Afterwards, the features are eventually used for training and prediction.

5 Experiments

There are totally five healthy subjects for our experiments, including four men and 1 woman, all of whom are around 23 years old. Particularly, we ensure that none of the subjects is color-blind. Each subject is asked to have sufficient sleep at night and get up early in the morning. Each experiment is conducted after lunch and lasts for 67 minutes so that the subject behaves sober at first and sleepy after a period of about half an hour in the experiment. The room is in silence and the light is soft.

As is stated in Section 2, the subject is asked to press the button with the same color as the traffic sign displayed on the screen. With the help of NeuroScan Stim Software, we can collect error rate data and EOG signals, as well as video images from the infrared camera.

We use LibSVM [16] to train and test data and use the square correlation coefficient and mean squared error to evaluate the model. The parameters of the SVM Model are selected as follows:

$$s = 3(\epsilon - \text{SVR}), \quad t = 2(\text{RBF kernel}), \quad c = 8, \quad g = 1/64, \quad p = 1/1024$$

Data for each subject is 400 points long. It is divided into 2 parts with the same length. After the data is divided, the first part is used as the testing set while the other one is used as the training set. Fig. 5 indicates the example of prediction result for the second part of the subject 1.

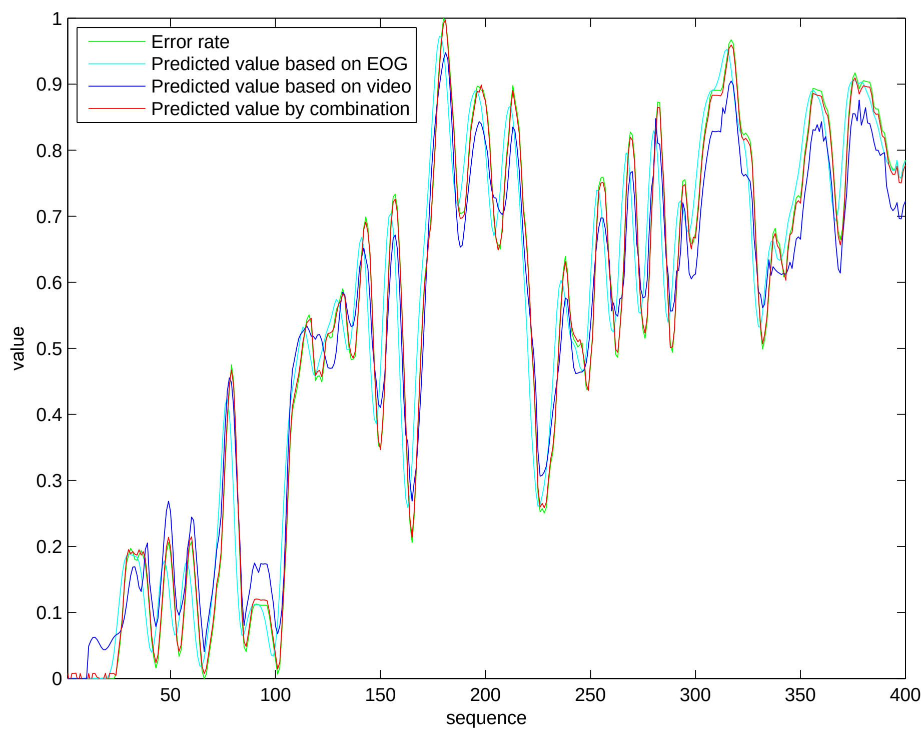


Fig. 5. Example of comparison between error rate and different prediction methods

The correlation and squared error are displayed in Table 1.

6 Conclusions and Future Work

In this paper, we have proposed a novel system for vigilance analysis based on both video and EOG features. From the experimental results, we can arrive at the conclusion

Table 1. Squared correlation coefficient and Mean squared error of regression result

Subject	Video-based	EOG-based	Combinination
1	$0.731/0.0256$	$0.843/0.0136$	**0.852/0.0117**
2	$0.778/0.0129$	$0.892/0.0064$	**0.919/0.0170**
3	$0.750/0.0151$	$0.866/0.0148$	**0.882/0.0111**
4	$0.750/0.0175$	$0.929/0.0091$	**0.937/0.0045**
5	$0.756/0.0170$	$0.809/0.0051$	**0.921/0.0072**
Average	$0.752/0.0882$	$0.88/0.0098$	**0.898/0.0089**

that our new method offers a good prediction of the actual error rate of the human being, which largely reflects the real vigilance level. Moreover, this method outperforms the existing approaches using either video features or EOG features alone, since our proposed method utilizes both the accuracy of EOG signals but the yawn state and body postures provided by video as well. In the future, we are planning to utilize comprehensive features including depth information and grip power to get a better performance. Besides, more experiments will be conducted and the stability and robustness of the algorithms is expected to be improved.

7 Acknowledgments

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