Electrooculography Signals to Find Driver Drowsiness

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Abstract— Study provides a new application of convolutional neural networks for drowsiness detection based on electrooculography (EOG) signals. Drowsiness is charged to be one of the major causes of traffic accidents. Such application is helpful to reduce losses of casualty and property. Most attempts at drowsiness detection based on EOG involve a feature extraction step, which is accounted as time-consuming task, and it is difficult to extract effective features.

An unsupervised learning is proposed to estimate driver fatigue based on EOG. This model automatically provide a more complete and appropriate set of features and our results show that combination of these features yields a better predictor of drowsiness. In this model, the LDS approach performs an important step for reduction of unfavorable disturbance of drowsiness-unrelated parts. A convolutional neural network with a linear regression layer is applied to EOG signals in order to avoid using of manual features. With a post-processing step of linear dynamic system (LDS),it is able to capture the physiological status shifting.

The performance of the proposed model is evaluated by the correlation coefficients between the final outputs and the local error rates of the subjects. Compared with the results of a manual ad-hoc feature extraction approach, CNN based method is proven to be effective for drowsiness detection.

Index Terms—electrooculography (EOG) signal, linear dynamic system, CNN based method, discrete wavelet transform

I. INTRODUCTION

Drowsiness refers to the state of near-sleep, a strong desire for sleep, or sleeping for unusually long periods. It is understood that a person in special situations, such as driving a car, operating a machine, needs to remain alert. Or if not, serious casualty may occur. According to the resent study performed in 2006 by the National Highway Traffic Safety Administration (NHTSA) and Virginia Tech Transportation Institute (VTTI) , nearly 80 percent of crashes and 65 percent of near-crashes involved some form of driver inattention. This study recognizes driving fatigue as one of the major cases of traffic accidents in the US. Thus, considering the various application scenarios, effective drowsiness detection model is in urgent need and has broad application prospects as well.

Various methods have been proposed to detect drowsiness, which can be divided into video based, multi-sensor based and physiological signal based. Among the video based methods, a method using the percentage of eyelid closure over the pupil over time , which turns out to be a valid psychophysiological measure of alertness. However, video based methods are sensitive to illumination changes and consequently fail to capture the driver's eyes. While both video based methods and multi-sensor based approaches fail to predict driver fatigue in advance, this implicitly signifies physiological signals based methods would be a better choice.

There are various researches on sleep based on physiological signals. In 1968, Rechtschaffen and Kales divided sleep into five stages (S1, S2, S3, S4, REM), plus the state of wakefulness (W), according to the features extracted from electroencephalogram (EEG), electrooculogram (EOG), and electromyogram (EMG) .Various drowsiness detection models based on EEG signals were proposed. Their results have shown that EEG based methods can correctly discriminate between wakefulness and sleepiness. Therefore, EEG based methods are recognized as golden standard for drowsiness detection. Despite the high accuracy of EEG based models for characterizing the drowsiness, EEG signal is regarded to be liable to be affected by noise and difficult to collect. Thus, by reasons of EOG signal's easiness to collect and immunization to slight noise, EOG based methods are considered as a compromise between accuracy and facility. EOG features mainly slow eye movements (SEM), to estimate vigilance changes during a monotonous task are used. Feature extraction and feature selection are the key stage in such process.

EOG-based method is enhanced by incorporating recent advances in machine learning with deep learning approaches. Convolutional neural network (CNN) has been widely used for this method which trains a large deep convolutional neural network to classify images. CNN is applicable to processing EOG signals. In this method, the ideas of deep learning approach to drowsiness detection are applied. It focuses on developing regression models of drowsiness detection by incorporating CNN based on electrooculography. it emphasize on building an unsupervised feature learning model for drowsiness detection as opposed to manual ad-hoc feature extraction process. it employ the experiments described practically, by collecting EOG signals of 22 participants, and preprocess the signals with noise removing and band pass filter. Then the raw EOG signals are fed up to the convolutional neural network. The weight matrices in each layer of convolutional neural network are trained in a layer wise greedy fashion with stacked convolutional auto-encoder. Such unsupervised training method has proved to reach awesome results in areas such as object recognition and speech recognition. Once the pre-training is finished, the local error rate is added to train the last regression layer. The final regression results are obtained by integrating a linear dynamic system to smooth the results and improve the performance by capturing a more reasonable vigilance state switching, and eliminating excessive or unlikely state transitions. Comparison between CNN and traditional manual feature extraction shows that CNN yields models of significantly higher correlation coefficients.

The detection process consists of four parts. First give an overview of the state-of-the-art drowsiness detection model, which is used for comparison, and then details methodology. In the third part, experiments setups and label acquisition are performed. Finally, results and analysis.

II. LITERATURE REVIEW

"EOG based drowsiness detection using CNN" paper describes, [1] a new application of convolutional neural networks for drowsiness detection based on electrooculography (EOG) signals. Such application is helpful to reduce losses of casualty and property. Most attempts at drowsiness detection based on EOG involve a feature extraction step, which is accounted as time-consuming task, and it is difficult to extract effective features. An unsupervised learning is proposed to estimate driver fatigue based on EOG. A convolutional neural network with a linear regression layer is applied to EOG signals in order to avoid using of manual features.

"Development of Vehicle Driver Drowsiness Detection System Using EOG" [2] paper helps to understand the use of electrooculogram (EOG) as an alternative to video-based systems in detecting eye activities caused by drowsiness. The EOG, which is the electrical signal generated by eye movements, is acquired by a mobile bio signal acquisition module and are processed offline using personal computer. Digital signal differentiation and simple information fusion techniques are used to detect signs of drowsiness in the EOG signal. EOG signal is found to be a promising drowsiness detector, with detection rate of more than 80%.

"Drowsiness detection based on visual signs" [3] paper gives an algorithm for drivers' drowsiness detection based on visual signs that can be extracted from the analysis of a high frame rate video . A study of different visual features on a consistent database is proposed to evaluate their relevancy to detect drowsiness by data-mining. It provides good results with more than 80% of good detections of drowsy states.

"The Design and Development of Drowsiness Detection System for Road Safety Improvement"[4] paper proposes a design and build of low cost blinking detection system by measuring the resting potential of the retina or electrooculography (EOG) signal. The EOG signals are sent out to a personal computer for motoring and processing the signals which develops on methods for detecting and interpreting eye blinks.

III. METHODOLOGY OF DROWSINESS DETECTION MODEL

Drowsiness reflects human's mental and bodily states. The state-of-the-art methods mainly contain five steps: preprocessing, feature extraction, feature selection, feature processing and regression (classifier) training and prediction. Part of the complexity of drowsiness detection model lies in designing the proper features or feature combination which are texted by conducting the experiment. The flow of the system can be shown as:

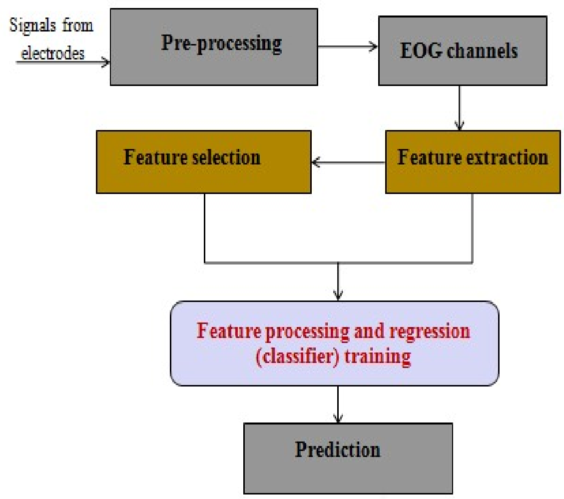

Fig 3.1 Flow diagram of State-of-the-art method

A. Preprocessing

Signals from electrodes are down sampled to 125 Hz at first. With the signals from four electrodes, it can easily obtain two EOG channels, the horizontal and the vertical, by substraction between the electrodes of the same color in Fig.3.1. Then signals are filtered with a band pass between 0.3 Hz and 10 Hz. Afterwards, mean value is subtracted. In the final step, signals are saturated at a saturation constant and scaled to 0 to 1. When the preprocessing is finished, noise is eliminated and signals are normalized.

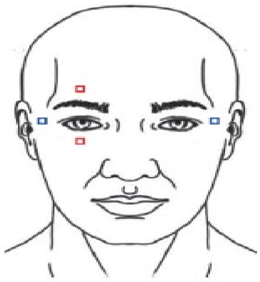

Fig 3.2 Representation of Placement of electrodes.

B. Feature Extraction

The existing manual ad-hoc features extracted from EOG mainly contain SEM features, blink features and energy features. Various extraction techniques have been employed to get the EOG features. Their extraction procedure mainly contains three steps, eye movement detection, feature extraction, and feature processing. Slow eye movement and blink are the most valuable eye movements correlated to fatigue. Features from these two eye movements are extracted and energy is used detect drowsiness.

The automatic detection technique of SEM developed by Magosso and colleagues were applied. This method is based on discrete wavelet transform (DWT) and includes three steps: wavelet decomposition, energy computation and discriminant function. Blink detection algorithm is an improved version of the double thresholds method. Two thresholds which represent the eyelid's closing speed and opening speed, respectively, are utilized to locate blink waveforms on the differences of vertical EOG.

Once the eye movements are detected, feature extraction is conducted. Table I is a list of features extracted for comparison. Since the energy of different frequency bands in the EOG can implicitly express the intensity of different kinds of eye movements, here use wavelet transformation to extract the ratio of low and high frequency energy on both horizontal and vertical EOGs. The extracted features from EOG with a time window of 8 seconds, and the detailed description of features is shown in Table 1.

feature	description
SEM proportion	SEM number
Closing time	duration of closing phase of blink
Closing PVe	peak velocity in closing phase of blink
Opening PVe	peak velocity in opening phase of blink
Closing MVe	mean velocity in closing phase of blink
Opening MVe	mean velocity in opening phase of blink
HEO LF/HF	PSD ratio between low and high frequency on horizontal channel
VEO LF/HF	PSD ratio between low and high frequency on vertical channel

Table 1. List of features extracted from EOG

C. Feature Processing and Regression

Due to the existence of noise in features, a linear dynamical system (LDS) approach is introduced in system, a semi supervised dynamic model, for smoothing and de-noising. Details of LDS will be introduced in section III-C. As features are obtained in the processes, a support vector machine for regression is employed. it utilized the library for support vector machines (LIBSVM) and search the parameters with grid strategy to ensure the best results. For the need of comparison, a full leave-one-out cross-validation of the 22 participants is done.

D. Experiment Description for Drowsiness Detection.

The whole experiment is about 70 minutes and 22 sessions are recorded from 22 different subjects. Subjects are required to get enough sleep at the night before the experiments. Conducted the experiments after lunch for the purpose that the subject is awake in the beginning and sleepy after about half an hour later.

Fig 3.3 Representation of the subject wearing electrodes

The subject's task is to simply push the correct button as soon as possible according to the color of the image displayed on the screen in a quiet room with soft lights. here use traffic signs in four colors which are red, yellow, blue and green. 640 different signs are selected with each color 160. On the screen, signs are shown for 0.5 seconds and screen turns black for a 5-7 seconds interval. When the experiment performs, the system automatically records the correctness of each response (no response will be considered as incorrect). Suppose to get higher error rate when the subject is drowsier, and a curve of error rate is obtained throughout the whole experiment. The local error rates are calculated by a 2-minute time window with a step of 8s.

In this experiment, EOG signals are recorded by the NeuroScan system. As is shown in Fig. 4, four electrodes on the EEG cap are used to collect the data. 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 top and the bottom ones. The signals are recorded using a 32-bit resolution and 500Hz sample rate.

E. Error Rate

In the experiment, the local error rate is used as the index of fatigue. The local error rate e(t) is derived by computing the target false recognition rate within a 2-min time window at 8-s step as

$$e(t) = \frac{NumF(ST + 2t - L/2, ST + 2t - 1 + L/2)}{NumT(ST + 2t - L/2, ST + 2t - 1 + L/2)} \quad (9)$$

where ST is the start time for fatigue measurement, L is the 120-s window length, NumF(i,j) is the number of false responses within the time window (i, j), and NumT(i,j) is the number of total stimuli within the time window (i, j). The result is represented by correlation coefficient of the regression result and the local error rate. ranges from -1 to 1. Higher absolute value indicates higher relevance. Is calculated as follows:

$$\gamma = \frac{Pt(f(t) - f(t))(e(t) - e(t))}{qPt(f(t) - f(t))2\_Pt(e(t) - e(t))2} \quad (10)$$

where f(t) and e(t) represent regression result and local error rate, respectively. f(t) and e(t) are their average over time.

IV. RESULTS

A. Comparison of Manual Ad-Hoc Features Extraction Method with CNN Based Methods

To show the efficiency of CNN based method, features extracted in both methods are applied on the EOG data set collected. More than 22 subjects have taken participate in the experiments. However, subjects who didn't show distinct fatigue during the experiments were eliminated. Performance was taken for the leave-one-out cross-validation to get the mean correlation coefficients which is regarded as the key index of drowsiness detection models. Comparison between the traditional model of pattern recognition and CNN models is presented to show model's advantages.

As is shown in manual ad-hoc model, the raw signals from the device are processed and scaled the signals to the range of 0 to 1. Two EOG channels, the horizontal and vertical, which are in the same range, are obtained and high frequency is removed. The training samples were randomly picked in the training sessions to balance the range of predictor variables.

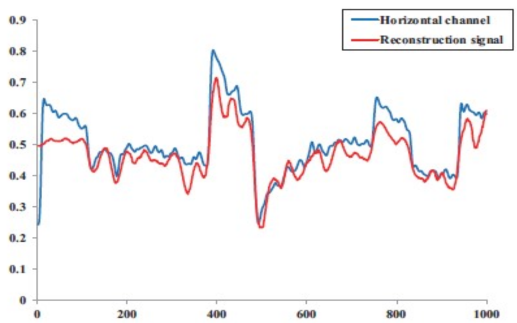

Fig 4.1 Horizontal channel

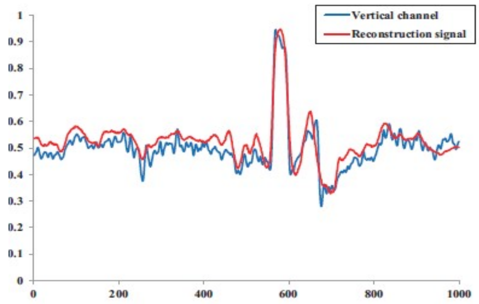

Fig 4.2 Vertical channel

The CNN trained contains two convolutional layers with 8 and 4 neurons, respectively, as well as max pooling layer over non-overlapping windows of size 8 and 2, respectively. On the consideration of overfitting, the topology of the network, which is competent to extract proper drowsiness-related features, was selected after preliminary experiments. Each neuron in the first and second convolutional layers has 201 and 26 inputs, respectively. the convolutional neural network were pertained using stacked convolutional auto-encoders with the same structure as the CNN. More than half of the correlation coefficients of the artificial network are slightly better or better than the statistical method and CNN based method gets a smaller standard deviation. These results indicate that CNN model processes an equivalent or even better abilities than the corresponding models built on commonly used ad-hoc statistical features on drowsiness detection.

V. CONCLUSION AND FUTURE SCOPE

The application of convolutional neural network were introduced to EOG-based drowsiness detection and proposed a new reliable drowsiness detection model in this paper. The model proposed employs two convolutional layers that learn to extract relevant features from the EOG signals. The EOG dataset is derived from 22 subjects of fatigue experiments. The experimental results on our EOG dataset showed that convolutional neural network possesses an equivalent or even better ability over manual ad-hoc feature extraction method on drowsiness detection task. Despite the manual designed features advantage in depicting eye movements and interpreting the physical properties of EOG, part of the features extracted through eye movements pattern detection by the deep neural networks is similar to the manual designed one, while other features are different from the manual designed and hard to design in practice. This model automatically provide a more complete and appropriate set of features and our results show that combination of these features yields a better predictor of drowsiness. In this model, the LDS approach performs an important step for reduction of unfavorable disturbance of drowsiness-unrelated parts. As a consequence, a remarkable increase in prediction accuracy is obtained.

It further demonstrates that convolutional neural network is applicable to physiological signals and deep learning methodologies are highly appropriate for drowsiness detection. This work also suggests that the trivial, tough and unstable feature extraction process in the traditional drowsiness detection model of pattern recognition can be redundant. With small modifications, the methodology proposed can be applied for online drowsiness detection model, which can be widely used in various scenarios. Future work includes a promotion of the topology of the network and tests on the parameter sets. Drowsiness detection models in other one-dimensional time series physiological signals such as EEG and EMG should be done and more experiments in other scenarios will be performed to test the generality of the drowsiness detection model.

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