Detection of Driving Fatigue Based on Grip Force on Steering Wheel with Wavelet Transformation and Support Vector Machine

Fan Li[1], Xiao-Wei Wang[1], and Bao-Liang Lu[1,2]

[1] Center for Brain-like Computing and Machine Intelligence
Department of Computer Science and Engineering
[2] MOE-Microsoft Key Lab. for Intelligent Computing and Intelligent Systems
Shanghai Jiao Tong University
800 Dongchuan Road, Shanghai 200240, P.R. China
bllu@sjtu.edu.cn

Abstract. This paper proposes an unobtrusive way to detect fatigue for drivers through grip forces on steering wheel. Simulated driving experiments are conducted in a refitted passenger car, during which grip forces of both hands are collected. Wavelet transformation is introduced to extract fatigue-related features from wavelet coefficients. We compare the performance of k-nearest neighbours, linear discriminant analysis, and support vector machine (SVM) on the task of discriminating drowsy and awake states. SVM with radial basis function reaches the best accuracy, 75% on average. The results show that variation in grip forces on steering wheel can be used to effectively detect drivers' fatigue.

Keywords: fatigue detection, grip force, wavelet transformation.

1 Introduction

The world vehicle population was reported to have surpassed the 1 billion-unit mark in 2010 (240 million in U.S. and 78 million in China) [1]. Automobile has been becoming the most important necessity for travel. However, accompanied with it is that more and more traffic accidents have happened. Driving fatigue has long been identified as one of the major causes of traffic accidents. It was founded that the crash risk was fourteen time higher for drives who had almost fallen behind the wheel [2]. According to National Highway Traffic and Safety Administration (NHTSA) report, driver fatigue and drowsiness causes 100,00 crashes annually, resulting in more than 40,000 injuries. If we can determine the onset of driving fatigue, such accidents can be avoided.

Most of the existing driving fatigue detection methods can be divided into three categories [3]:

1) Physical and physiological data of drivers are used to detect their driving fatigue. These include the Electroencephalography (EEG), Electrooculography (EOG) and eye patterns and head movement by video [4]. PERCLOS

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(PERcent eyelid CLOSure), put forward by Carnegie Melon Driving Research Center, is one of the most effective measure for driving fatigue detection [5].
2) Driving performance is indirectly assessed by raw rate, lateral position and longitude speed. Daimler Chrysler [6] has developed a detection algorithm that jointly analyzed these signals to detect drivers' fatigue.
3) Drivers in drowsy status would handle steering wheel and tread pedals (gas, brake and clutch) more slowly and improperly than in sober state [3,7,8]. Drivers would diminish grip force when falling into drowsy, even loosen the steering wheel fully, which could easily lead to accident. Thum Chia Chieh [7] proposed a statistical method to accumulate the logarithm of probability ratio of staying in drowsy or awake state. But the model was too simple to work well. Eskandarian and Mortazavi [8] trained an artificial neural network to detect drivers' fatigue, based on the hypothesis that under a drowsy state, the steering wheel movements become less precise and larger in amplitude. The proposed method had a big default that he did not fully consider time-order of steering wheel angle, which would lower detection accuracy.

Vigilance, the ability to maintain attention and alertness over prolonged periods of time, is an effect measurement of fatigue. In this paper, a simulated driving system was designed and subjects were asked to finish driving task in a real car. We collected drivers' grip force and response time to an audio signal which was used to measure drivers' vigilance while driving. We proposed an effective feature extraction method to extract features from time domain and wavelet coefficients through wavelet transformation. We compared the performance of three classifiers — support vector machine (SVM), linear discriminant analysis (LDA) and k-nearest neighbours (KNN), on the task of discriminating drowsy and awake states.

2 Experiment

2.1 Platform

Grip Force Detection
The setup for grip force detection is shown in Fig. 1. The wheel is fully covered by two pieces of force sensors to detect drivers' force of left and right hands. The force sensitive resistor (FSR) was available from Interlink Electronics, which is a very thin polymer thick film (PTR) device and will give little influence on driving. When force applied to its active surface, its resistance decreases. The resistance is converted to voltage through a simple resistance to voltage converter circuit. The output voltage V_{out} characterizes the force exerted on the wheel, and is collected by a commercial USB collection card with a multi-channel AD chip to PC for analysis. The sampling rate is 100 Hz for each hand's force.

Simulated Driving System
A car has been refitted for experiment. The car's driving operational devices (wheel and pedals) were replaced with Logitech's simulated controllers, whose

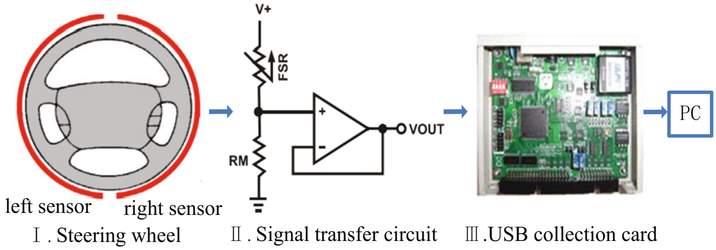

Fig. 1. Platform of detecting grip force of steering wheel

size and operation way are similar to real ones. We have developed a simulated driving software to imitate complex driving scenes with different weather, road conditions on a large LCD screen to cover subject's sight. The driving state parameters, such as driving speed, steering wheel angle, in curved or straight road and so on, will be recorded. Video cameras are installed to record subjects' face status and hand action, which can be aided to determine whether the subject is in a drowsy state.

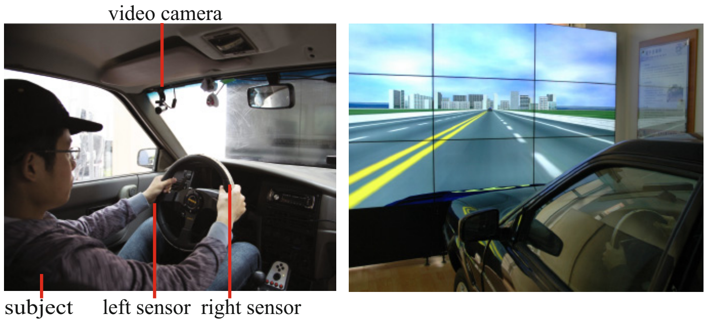

Fig. 2. Platform of simulated driving system

2.2 Procedure and Subjects

As shown in Fig. 2, subjects sit in the driver's seat to finish a two-hour-long driving task. They are asked to drive carefully to avoid crash with other cars. To measure subjects' vigilance, they need to do a periodical audio task which would not influence driving [9]. Fig. 3 shows the trial sequence. The trail period is 20 sec, and in the second half period, it will randomly play a two-second-long frog-croak sound. Once hear frog-croak, the subject would tread a special pedal with a resistance. When the pedal is trodden, its resistance value decreases, then through the same transfer circuit and USB collection card in Fig. 1, tread signal is recorded. During experiment, if the subject has fallen into sleep, he or she would be waken up to get a transitory sober status and restart driving. Four

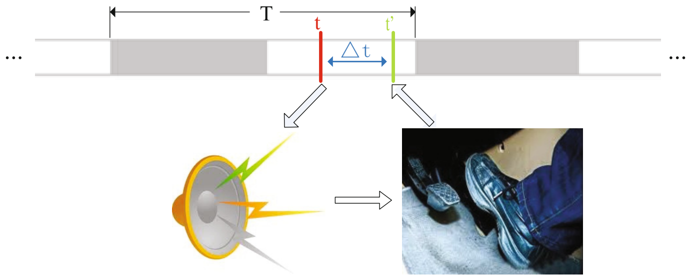

Fig. 3. The vigilance task. Trial period T is 20 s, t is the time of producing sound, t' is the tread time of subject, and Δt = t − t' is the response time.

healthy subjects of 19-25 years old have participated in this experiment for twice and the interval was one week. Experiments were carried out in a sound-proof room during 20:00 – 22:00 pm.

2.3 Data Collection

For each experiment, steering wheel angle signal is recorded by driving software at 100 Hz. Grip Force and tread signals are sampled by USB collection card at 100 Hz. And the time of sound played is recorded by PC, which is accurate to 1 millisecond. All these signals would be down sampled at 10 Hz and enough time stamps are made to synchronize them.

2.4 Vigilance Measurement

To train an effective fatigue detection method, reference vigilance indexes are necessary for supervised learning. In our experiment, the reaction time Δt_i of i-th trial can be used as reference vigilance level in that trial period, for there is an increase in average reaction time when the subject is becoming drowsy in vigilance task [10]. Because the cycle length of vigilance's fluctuation is usually longer than 4 min [11], to eliminate the variation of reaction time, we use a triangle weighted moving average (WMA) method to measure vigilance value in i-th trial period within a 2-min window:

$$vigilance_i = \frac{\sum_{j=i-3}^{i+3} (4 - |i-j|)\Delta t_j}{\sum_{j=i-3}^{i+3} (4 - |i-j|)} \tag{1}$$

Fig. 4 shows the vigilance curve after WMA for one experiment.

3 Method

3.1 Feature Extraction

The original signals we collect are two channels of time-varied grip force, through which it is difficult to detect the subject's temporal vigilance level. We can

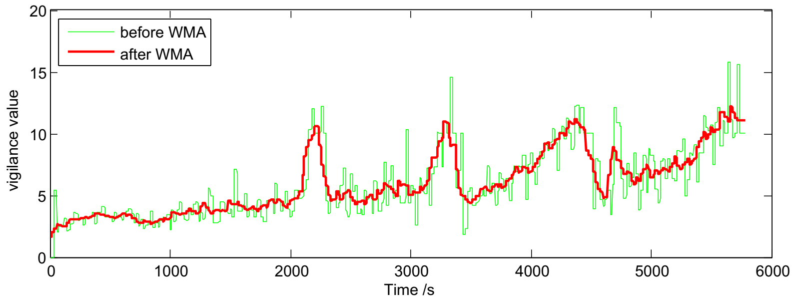

Fig. 4. Vigilance value represented by reaction time. The green curve is the original reaction time, and the red curve is the reaction time after WMA.

extract fatigue-related features in time domain and from wavelet coefficients of original signals through wavelet transformation.

The time-window length for one sample we choose is 25.6 sec. For the sample frequency is 10 Hz and interval is 0.1 sec, in a sample window, there are 256 data points of force, thus it is convenient to make 8-level wavelet transformation. And the moved step for sample windows is 6.4 sec, quarter of the length of a sample window.

Four kinds of statistical features are extracted in time domain. They are maximal value, minimal value, mean value and standard deviation, which can roughly characterize the range of force.

Because wavelet transformation is localized in both time and frequency, it can characterize the power spectrum in frequency domain. Haar wavelet function is chosen, so wavelet coefficients at i-th level, which characterize variation of signal in the corresponding time scale, can be calculated:

$$c_{ij} = r \cdot \left(\sum_{k=(j-1)\cdot 2^i+1}^{(j-1)\cdot 2^i+2^{i-1}} a_k - \sum_{(j-1)\cdot 2^i+2^{i-1}+1}^{j\cdot 2^i} a_k \right) \tag{2}$$

where $i = 1, 2, \ldots, 8$, $j = 1, 2, \ldots, \frac{l}{2^i}$, $l = 256$, and r is a positive normalization coefficient. The following features can be extracted from wavelet coefficients at i-th level to represent the time-frequency distribution of force signals:

1) Square sum of the wavelet coefficients, which represents the power of force signals in the corresponding frequency band.

$$p_i = \sum_j c_{ij}^2 \tag{3}$$

2) Ratio of positive coefficients in the whole wavelet coefficients.

$$pr_i = \frac{\sum_j 1 \cdot \{c_{ij} > 0\}}{\sum_j 1} \tag{4}$$

When grip force is increased, corresponding coefficient will be positive. It represents the time proportion of increasing grip force.

3) Ratio of sum of positive coefficients to sum of absolute value of negative coefficients, which characterizes the amount of increased force relative to decreased force. To calculate conveniently, logarithm value is used.

$$lpnr_i = \log_{10} \frac{\sum_j |c_{ij}| \cdot \{c_{ij} > 0\}}{\sum_j |c_{ij}| \cdot \{c_{ij} < 0\}} \tag{5}$$

Therefore, a total of 56 features can be extracted from two channels of force signals.

3.2 Classification

There exits difference in each subject's fatigue mode, so original labeled vigilance value was regularized firstly. By referring to recorded driving video, a specified threshold was chosen to determine whether the subject was stay in drowsy or awake status for each subject. In a two-hour-long experiment, there are about 700 cases.

We classified samples using three kinds of algorithms, k-nearest neighbors (KNN), linear discriminant analysis (LDA) classification and support vector machine (SVM). KNN is a non-parametric method for classifying the test case based on k most nearest training example. LDA is a linear classifier based on statistical characteristics of the training samples. SVM maps the input features into another feature space using kernel function, and iteratively approaches the optimal hyperplane with maximal margins. LIBSVM [12] was the tool to train SVM classifier we used, and the selected kernels were linear and radial basis function (RBF). At first, we employed these algorithms within one single experiment's samples. 3/4 samples were randomly chosen from drowsy set and awake set respectively as training samples, and the other as test samples. Then we attempted to use samples of the first experiment as training set to predict samples of the second experiment.

4 Results and Discussions

The classification performance of the aforementioned classifiers is listed in Table 1 and Table 2. Accuracies within one single experiment are higher than that between two experiments of one subject, due to strong correlation of force signals in one single experiment. The performance of LDA is close to SVMs, because of the fact that one sample only contains time sequence with 512 data points of grip force, a linear classifier with the 56 original features is sufficient to characterize the influence of subject's fatigue on grip forces. KNN is the worst one, and the accuracy of SVM-RBF is higher than SVM-linear and LDA, for it maps original features into more complex feature space. The performance of these classifiers is different among subjects.

Table 1. Classification accuracies of different classifiers within one single experiment

Classifier	Subject 1	Subject 2	Subject 3	Subject 4	Average
KNN	0.695	0.800	0.692	0.784	0.742
LDA	0.853	0.877	0.757	0.830	0.829
SVM-linear	0.848	**0.890**	0.757	0.824	0.830
SVM-RBF	**0.856**	0.862	**0.758**	**0.855**	**0.833**

Table 2. Classification accuracies of different classifiers between two experiments

Classifier	Subject 1	Subject 2	Subject 3	Subject 4	Average
KNN	0.652	0.686	0.636	0.677	0.663
LDA	0.720	**0.804**	0.670	0.680	0.719
SVM-linear	0.733	0.795	0.642	0.740	0.727
SVM-RBF	**0.751**	0.793	**0.674**	**0.783**	**0.750**

5 Conclusion

In this paper, we have proposed an unobtrusive drivers' fatigue detection method based on grip force on steering wheel. Wavelet transformation was used to extract fatigue-related features. By comparing performance of three kinds of classifiers, SVM with radial basis function reaches the best accuracy, but it needs more time for training model and detecting fatigue in practice. As a trade-off, SVM with linear kernel is preferred, for it is faster and owns a good classification accuracy. The experiment was conducted in a simulated environment, and in the future, we will conduct experiment in real driving environment to check the feasibility of the proposed method.

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