

# Real Time Drowsiness Detection Based on Lateral Distance using Wavelet Transform and Neural Network

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**Abstract**— The paper proposed a model using real time driving front video recording to detect driver drowsiness. The video recordings were fed into the TRW's simulator to obtain the lane-related signals. Time domain features and frequency domain features were extracted from the lane-related signals to characterize the difference of alert state and drowsiness state. Both support vector machine and neural network were used to detect the drowsiness. Real world driving data from multiple objects were collected for the performance evaluation. Both face view video recordings and front view video recordings were made. The lane related signals were extracted by feeding the front view video recordings into the TRW simulator. Experimental results on real world driving recordings illustrated that the proposed method can detect the drowsiness with an accuracy over 90%. Both inner-driver and cross-driver testing results were provided. It also show that TRW simulator can generate reliable lane related signals if high quality video sequences are provided.

## I. INTRODUCTION

According to the National Sleep Foundation's 2005 Sleep in America poll, 60% of adult drivers – about 168 million people – say they have driven a vehicle while feeling drowsy in the past year, and more than one-third, (37% or 103 million people), have actually fallen asleep at the wheel. In fact, of those who have nodded off, 13% say they have done so at least once a month. Four percent – approximately eleven million drivers – admit they have had an accident or near accident because they dozed off or were too tired to drive.

The National Highway Traffic Safety Administration conservatively estimates that 100,000 police-reported crashes are the direct result of driver fatigue each year. This results in an estimated 1,550 deaths, 71,000 injuries, and \$12.5 billion in monetary losses [1].

Inattentive driving is a growing problem and drowsiness detection has become the research focus in these years. The study of drowsiness detection can provide the wealth of information for active safety features even autonomy driving in the future. Various systems have been developed to prevent driver falling asleep during driving [2-4]. Some of these are based on physiological signal from driver, which involve the

monitoring of activity in the brain, the heart and/or the eyes, like ECG, EEG, eye closure duration [5-10]. PERCLOS (percentage of time the eyes are more than 80% closed) is known as a very effective parameter in the drowsiness detection [11-14].

In order to collect these signals, the driver needs to wear high-end physiological signal sensors to get accurate signals, which is difficult during real time driving environment and is cost-expensive. Thus, non-intrusion method, such as computer vision-based method is a desirable option.

Due to the fact that, real world driving data with drowsiness is very difficult to obtain, simulation methodologies (with simulated driving environment) applied to training and testing in the field of drowsiness detection were widely used. A set of 3 screens with re-configurable positions can provide different angles of vision of drivers. The screen shows different scenarios to monitor the testing road [15, 16]. Monitoring is good simulation method but it is hard in commercial use and also the examining scenario is a simplified version of the actual situation [17]. There is few work which uses real word driving data. Fabian and Bin proposed new features for detection drowsiness for real world driving [18]. They analyzed the correlation between lane related features and Karolinska Sleepiness Scale (KSS). However, the classification error for three classes (drowsiness, alert, and questionable) is quite large.

In this paper, a drowsiness detection method using real driving data was proposed. Two cameras, one for front view and another for face view, were used to capture the video signals. The video signals from the front view were used to extract the drowsiness-related features. And the video signals from the face view were used to label the ground truth of drowsiness. Instead of designing new signal detection methods from the front camera signals, the videos were feed into the TRW simulator to generate the signals, such as the vehicle position, heading, lane position, lane detection quality, etc. The proposed method extracted time and frequency domains statistical features from the lateral distance signal and used neural network and support vector machine to detect the drowsiness.

Section II will describe the acquisition system - Transportable Instrumentation Package (TIP) equipment as well as the label of ground truth. The detail signal description will show on Section III. Section IV will introduce the methodology of drowsiness detection, the general algorithms and technics based on machine learning algorithm. After that, the experimental results are shown in Section V. Finally the conclusion and future work are presented in Section VI.

## II. DATA ACQUISITION SYSTEM AND GROUND TRUTH

The purpose of this section is to show a portable extendable and robust data acquisition system and to explain the methodology carried out to label the recording video and analysis task to evaluate drowsiness in professional drivers.

### A. Transportable Instrumentation Package (TIP) data acquisition system

TIP System is a portable data collection system that is easy in hardware installation and configuration in driver's car [19]. It is portable, extendable and robust. The system is built up with multi-channel synchronization equipment from Race Technology including video cameras, Controller Area Network (CAN) message and physiological signal. Fig.1 shows the TIP system in-vehicle device structure and configuration. In our experiment, we only used the multi-channel camera to generate front video and driver's face video for labeling. All the real driving data was collected by the TIP system. After each recording, the videos from the front view camera and the face view camera were synchronized. The videos from the face view camera were used to label the ground truth of driver's drowsiness states, and the videos from the front view camera were used for drowsiness-related signal extraction.

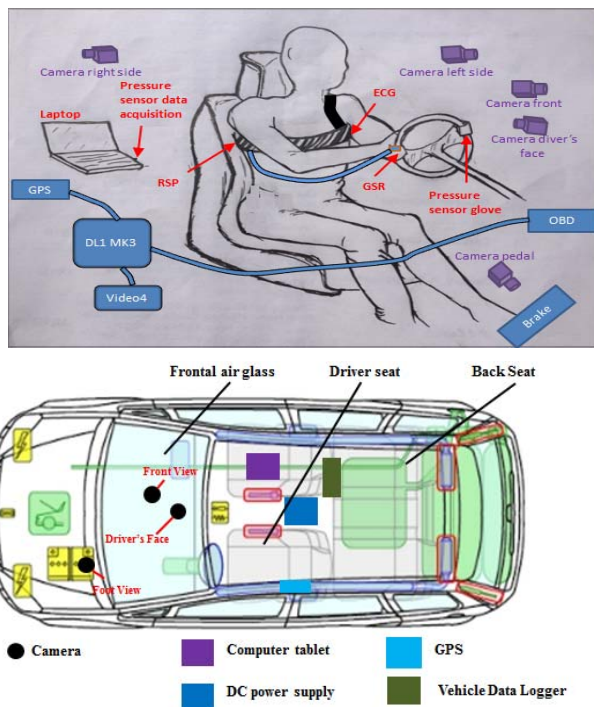


Fig. 1. TIP System in-vehicle Device Structure and Configuration

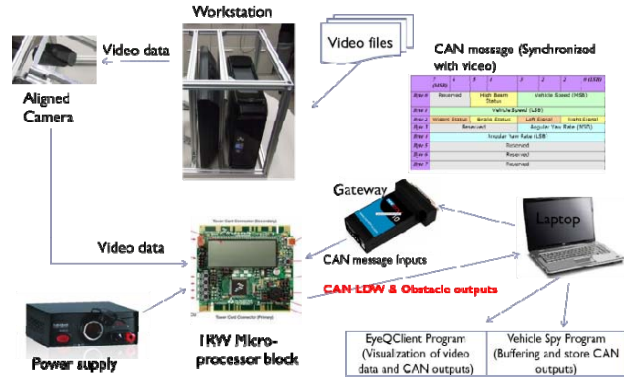


Fig. 2. Video Simulator System



Fig. 3. Visualization of system output

### B. Extraction Signals using TRW Simulator

The videos from the front view camera provide rich information of the road, vehicle, and the environment. For the application of drowsiness detection, the vehicle and road related signals are our primary concern. Various computer vision-based methods have been proposed to extract these signals from the video, such as the trajectory [12]. In this paper, TRW's simulator was used to achieve this purpose. The reason of using TRW's simulator is that this paper is also intended to evaluate if TRW's simulator can generate reliable signals from given videos for the application of drowsiness detection.

Fig. 2 shows signal extraction system, which consists of TRW simulator, laptop (to control the simulator, and to receive the extracted signals from the simulator), power supply, monitor, etc. The system is able to analysis the lane markers and lane positions via image processing techniques provided by EyeQClient software [20]. The message (signals) received by the laptop is recorded and decoded by Vehicle Spy Software [21]. Fig. 3 shows an example of visualization outputs. In the visualization screen, there are many signals and indicators. Table I lists part of the available signals and indicators. The

final signals, e.g., lateral distance, will be calculated from the signals listed in Table 1.

TABLE I. ENVIRONMENTAL SIGNAL-TRW SIMULATOR OUPUTS

LDW output	Description	Unit	Value range
Curvature	Lane Curvature	1/m	-0.0065572 ~ 0.0065571
Curve_deriv	Lane Curvature derivative	1/m <sup>2</sup>	-0.00131072 ~ 0.00131071
Heading	Lane Heading angle	Radians	-0.16384 ~ 0.16384
Confidence	Lane detection confidence score	Enum	0 ~ invalid, 1 ~ valid (only if one of the lane has high quality)
left_type	Left lane type	N/A	0 ~ dashed, 1 ~ solid, 2 ~ undecided, 3 ~ road edge, 4 ~ double/triple lane mark, 5 ~ Botts'dots, 6 ~ invalid
left_quality	Left lane detection quality	N/A	0,1 ~ low quality, 2,3~high quality
left_model_degree	Left lane model degree	N/A	0 ~ parabolic, 1 ~ linear, 2 ~ 3rd degree polynomial
left_pos	Left lane lateral position	m	-10.24 ~ 10.24
left_view_range	Maximal physical view range of left lane mark	1/256 m	0 ~ 127.996 m
right_type	Right lane type	N/A	0 ~ dashed, 1~ solid, 2 ~ undecided, 3 ~ road edge, 4 ~ double/triple lane mark, 5 ~ Botts'dots, 6 ~ invalid
right_quality	Right lane detection quality	N/A	0,1 ~ low quality, 2,3~high quality
right_model_degree	Right lane model degree	N/A	0 ~ parabolic, 1 ~ linear, 2 ~ 3rd degree polynomial
right_pos (C)	Right lane lateral position	m	-10.24 ~ 10.24
right_view_range	Maximal physical view range of right lane mark	1/256 m	0 ~ 127.996 m

### C. Drowsiness ground truth

Two methods were considered when labeling the ground truth. One is Karolinska Sleepiness Scale (KSS) level provided by the driver. The test drivers estimated their level of sleepiness according to the KSS, which has been proven, has high correlation to driving performance. The KSS level was generated by every 5 minutes based on questionnaire after driving. Another is labeling results (manually) from video sequence by our volunteers. During the labeling, the volunteers were asked to watch the videos (frame-by-frame) from the face camera, and to find any drowsiness events, such as eye-closing, yawning, nodding, etc. The timestamps of every drowsiness were recorded by our own labeling program. Also the labeling results were double checked by other volunteers.

The fatigue level is calculated by the number of seconds fatigue events, like nodding, eye closeness, yawning, happened in 1 minute. Table II shows the rules for ground truth labeling.

### III. METHOD AND ARCHITECTURE OF THE SYSTEM

In this section, data cleaning, feature extraction techniques, selected signals and statistical features will be elaborated. Then, the drowsiness detection system using either neural network or

TABLE I. LABEL EVENT DESCRIPTION

Event - Driver	Category
Yawning	Fatigue
Eye closing	Fatigue
Nodding	Fatigue
Head rotation(left/right) while changing lanes	Normal
Gaze movement(left/right) while changing lanes	Normal
Head rotation (up/down/left/right)	Active distraction
Gaze movement (up/down/left/right)	Active distraction
Body movement (Grab things, picking up phone, turning on/off radio, etc.)	Active distraction
Talk with passenger/Talk to the phone/Texting	Inattention
Event - Front view	
Lane change	Inattention
Approaching vehicle in front	

support vector machine is given. The following section describes the procedure of the proposed drowsiness detection method.

#### A. Signal description and data cleaning

The decoded message from the simulator provides *lane position*, *lane curvature*, and *lane curvature derivative*, which will be used to calculate the lateral distance. The lateral distance is computed via (1) according to the manual of TRW's simulator,

$$D_{lateral} = d_c \times Z^3 + C \times Z^2 + H \times Z + L_{pos} \quad (1)$$

Where  $C$  represents the lane curvature,  $d_c$  is the derivative of lane curvature,  $H$  is lane heading angle, and  $L_{pos}$  is the left/right lane position. The lane position is with regard to the lane center, from the midpoint of the driven lane to the longitudinal centerline of the vehicle. Using a right-handed coordinate system, distance to the right of the midpoint is positive and to the left is negative.  $Z$  is the distance between lateral distance calculation point and the camera position. We fixed  $Z$  to 40 here.

It should be mentioned that the output signals' quality depends on the video quality. That is to say, for low quality video, the lane boundaries cannot be detected correctly. Thus, before feature extraction, preprocessing methods must be applied to the signals (lateral distance) to clean and filter the outliers or missing data. Fig. 4 shows the steps of data cleaning for the system.

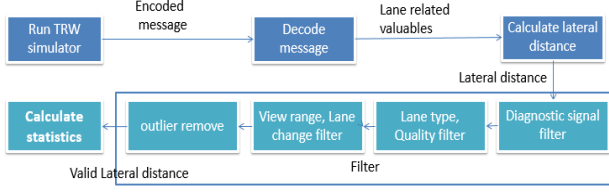


Fig. 4. Data cleaning process flow chart

- Diagnostic signal filter

Based on the LKA common CAN protocol, there are 6 diagnostics indicator, including blur images, low sun, partial blockage, partial transparent, out of calibration and auto fix status. Those 6 filters are provided by the software using image processing methods, and it provided three status including passed, failed and invalid. We only used the video data with the “passed” status to remove the low quality video frames because of the light, weather or other environmental issues which may result in unreliable detection of trajectory.

- Lane detection quality filters

There are 6 types of lane detected in the system. Applying the lane type filter, only dashed or solid lane is remained. Other lane types will be filtered out, like road edge, undecided, double /triple lane and so on. From the image processing perspective, based on the detection accuracy of the line, the quality is provided by the software ranging from 0 to 4, corresponding to the lane detection quality of low to high. For lane detection quality equals to 0, the detected lane information is not reliable. In our experiments, the signal points with lane detection quality higher than 1 were kept.

- Lane change filter

Normal lane change, merge, exit, etc., have a large effect on the lateral distance. In order to eliminate these effect, data points of 5s before and 5s after lane crossing point (LCP) were removed. The LCP represents the point where the vehicle crosses the border, and is manually labeled by our volunteers. Fig. 5 shows an example of LCP. Also, other events, which may affect the calculation of lateral distance were also removed, such as merge, exit, entry, etc.

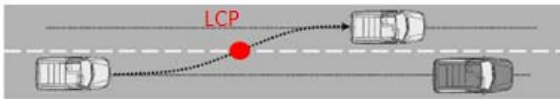


Fig. 5. Lane Crossing Point

- Outlier remove

Regarding to the outliers, we identified them according to the normal ranges recommended by the TRW’s manual. The outliers were simply removed and

interpolated back using linear method, if the number of successive outliers is low.

Fig. 6 shows an example of data cleaning result. The figure on the top is the decoded lane position signal without any processing. After applying the above filters, we are able to filter out the valid segment for the experiment. Fig. 6 shows the derivate of lateral distance  $D_{lateral}^{diff}$  (at the bottom).

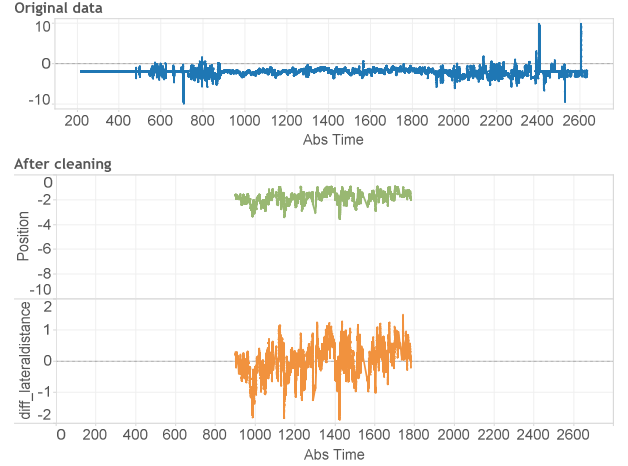


Fig. 6. Example Results of data cleaning and filter processing

## B. Feature extraction

### 1) Time domain Features

The first type of feature is extracted from the time domain signals, e.g., lateral distance. Before feature extraction, the signal is divided into windows with the window size of  $s_w$  and step size of  $s_{step}$ , and the mean normalization is applied to each window as follows,

$$\mu_w^i = \frac{1}{s_w} \sum_{j=i}^{i+s_w} D_{lateral}^j(j) \quad (2)$$

$$\overline{D}_{lateral}^i = D_{lateral}^i - \mu_w^i \quad (3)$$

where  $D_{lateral}^i$  represent the lateral distance of the  $i^{th}$  window. Within each window after mean normalization, five statistical features were extracted as follows. Fig. 7 shows an example of the moving window-based feature extraction method.

- LANEAVG( $i$ ): Average of absolute value of  $D_{lateral}^i$
- LANESTD( $i$ ): Standard deviation of  $D_{lateral}^i$
- LANEMAX( $i$ ): max value of  $D_{lateral}^i$
- LANESKEW( $i$ ): skewness of  $D_{lateral}^i$

- LANEKURT( $i$ ): kurtosis of  $D_{lateral}^i$



Fig. 7. Statistics feature calculation demonstration

## 2) Frequency domain features

By noticing that lane trajectory for drowsiness driving is a pseudo-periodic signal. Therefore, frequency analysis can be used to explore any event occurs in frequency domain. Discrete wavelet analysis is one of the most popular method as it has higher temporal resolution compared to discrete Fourier analysis. In this paper, 3-level wavelet analysis is used to decompose the time domain signal into multi-scales frequency signals.

Given a signal  $s$  of length  $N$ . The first step produces, starting from  $s$ , two sets of coefficients: approximation coefficients  $CA_j$ , and detail coefficients  $CD_j$ . These vectors are obtained by convolving  $s$  with the low-pass filter  $Lo_D$  for approximation, and with the high-pass filter  $Hi_D$  for detail, followed by dyadic decimation (down sampling) [22]. The next step splits the approximation coefficients  $ca_j$  in two parts using the same scheme, replacing  $s$  by  $ca_j$ , and producing  $ca_2$  and  $cd_2$ , and so on. The wavelet decomposition of the signal  $s$  analyzed at level  $j$  has the following structure:  $[cA_j, cD_j, \dots, cD_1]$  shown in Fig. 8.

After the frequency signals are available, five statistical features described in Section III-B-1) are extracted from them. The frequency features combining with the time domain features were used as the input of the classifier described in the next section.

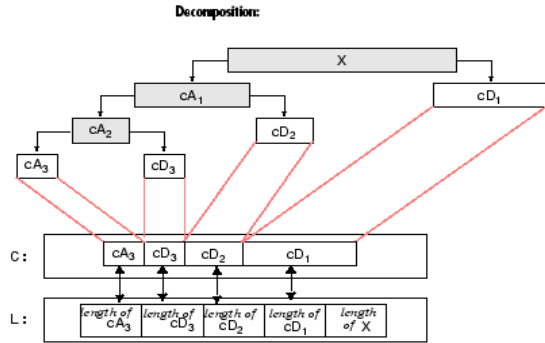


Fig. 8. decomposition structure

## C. Classification model

To detect the drowsiness by given feature vectors, two popular classification methods were evaluated in this paper. One is Support Vector Machine (SVM) for binary class classification with Gaussian RBF and kernel function due to its good performance in various applications. The other

classification algorithm is multi-layer artificial Neural Network (NN). The structure of neural network is shown in Fig. 9.

## D. Real time prediction and testing

In order to evaluate the performance of the proposed method on real time prediction and classification, a different video (different from the training sets) was used. To detect the drowsiness level at time  $t$ , the feature vectors extraction from the time period of  $[t, t - t_s]$  were feed into the system, where  $t_s$  represents window size in seconds for feature extraction. The output of the system represents the drowsiness level of the driver at time  $t$ . Two stages were involved in determining whether the driver is drowsy or not in each period, e.g., 30s. Fig. 10 shows the example of the stages, and the summary of these two stages are given as follows,

- Stage1: For each time stamp  $t$ , extract the feature vectors from the previous  $t_s$  seconds, e.g., 30s, and feed the feature vectors into the system to obtain the initial predictions at every 1s.
- Stage2: For every  $t_s$  s (e.g., 30s), majority voting is applied to the initial predictions. The voting result represents the final output of the prediction.

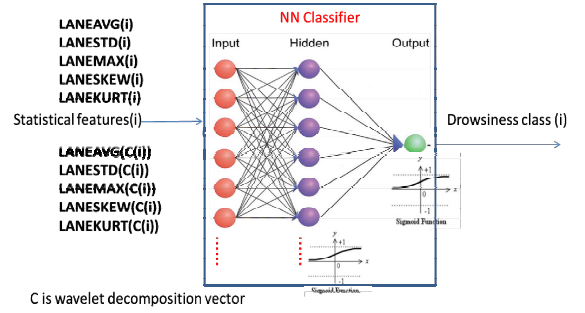


Fig. 9. Neural network architecture

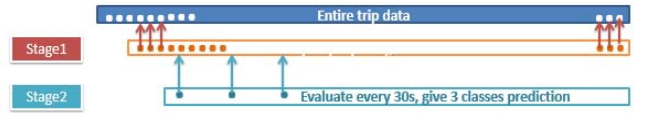


Fig. 10. Two stages real time prediction

## IV. EXPERIMENTAL RESULTS

In order to evaluate the performance of the proposed method, 65 real-world driving data recordings from 15 subjects were collected using our TIP system. The average lengths of driving is around 30 minutes. Most of driving data is collected on highway.

The ages of subjects are from 20 to 65. All of the drivers had more than two year driving experience and with professional driving skill. There are 33 complete and valid data recordings for 9 subjects. The signals used for feature extraction has the sampling frequency of 10Hz.

According to the labeling results and the self-claim of the drivers, only two drivers showing period of drowsiness. The driving data is labeled with predefined driver state events, based on workload-stress measure and also evaluated by questionnaire based on KSS score. Table III shows the data sets used in our experiments.

Two measurements were used to evaluate the performance of the proposed method: True Positive Rate (TPR), which means the rate of the drowsiness is correctly detected as drowsiness, and True Negative Rate (TNR), which means the rate of the alert is correctly detected as alert. The experimental results with different classification methods are presented in the following sections. Accuracy (rate correctly classified) is also used to represent its overall performance.

TABLE III DATA DESCRIPTION FOR EXPERIMENT

Driver ID	Date	length	Fatigue or not
ID0	02/13/2014AM	32min	Not drowsy
ID13	08/06/2014PM	35min	Not drowsy
ID5	12/05/2013	33 min	Drowsy
ID5	03/13/2014	39min	Not drowsy

#### A. Determining the optimal window size

Drowsiness state usually last for a period, from seconds to minutes. To characterize the drowsiness level, a larger window size of feature extraction is required. However, large window size will result in false negatives if the drowsiness only lasts for a very short period (less than the window size). In this section, the optimal window size which results in the best performance is determined. Fig. 11 shows the classification performance using SVM with various window sizes range from 100 (10s) to 300 (30s) on driver ID5. It can be observed that when the window size increases, both the TPR and TNR increase. The optimal performance is obtained when the window size is 300. Therefore, window size of 30s is used in all the experiments in the following sections.

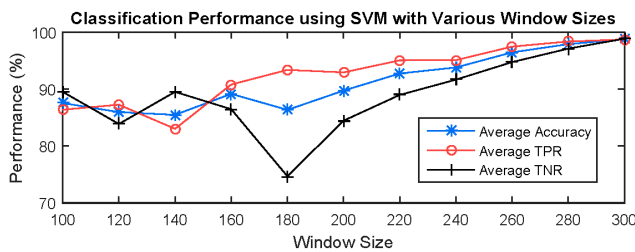


Fig. 11. Classification performance with different window sizes

#### B. SVM model using one driver recordings

The dataset used here is one driver (ID5) driving video at two different days. One is very drowsy driving and the other is alert driving. There are total 8809 drowsiness data points and 6649 non drowsy data points. We randomly pick 2/3 of all of data points as training data and the other 1/3 data points as testing data. The prediction rate achieves 99% in this

experiment and confusion matrix is shown in TABLE IV. The result for same driver is quite high from the result.

#### C. SVM model using multiple drivers recordings

We applied the support vector machine algorithm to multiple drivers to detect driver drowsiness. The videos in the system are from 3 drivers including one drowsy video from ID5 and 3 non-drowsy videos from ID5, ID0 and ID13. The data points are randomly divided to three folders. We used 2/3 of data to train the system and the other 1/3 are used to test. The testing data are not used in training. To compare the result, we did 3 fold cross validation and the result is shown in TABLE V, VI and VII. The prediction rate is around 90%.

TABLE IV ONE DRIVER PREDICTION RESULT (ID5)

Truth \ Prediction	Drowsy	Alert
	Drowsy	2607
Alert	11	1725

TABLE V CONFUSION MATRIX OF SVM CLASSIFICATION (1<sup>ST</sup> CROSS VALIDATION)

Accuracy: 90.32%		
Truth \ Prediction	Drowsy	Alert
	Drowsy	2515
Alert	738	9501

TABLE VI CONFUSION MATRIX OF SVM CLASSIFICATION (2<sup>RD</sup> CROSS VALIDATION)

Accuracy: 90.48%		
Truth \ Prediction	Drowsy	Alert
	Drowsy	2516
Alert	707	9521

TABLE VII CONFUSION MATRIX OF SVM CLASSIFICATION (3<sup>RD</sup> CROSS VALIDATION)

Accuracy: 90.41%		
Truth \ Prediction	Drowsy	Alert
	Drowsy	2514
Alert	707	9514

#### D. Neural network model using multiple drivers recordings

The training and testing data set is the same as the Section IV-C in TABLE V-VII but with neural network classification. The result for the detection rate is much higher than support vector machine. The results are shown in TABLE VIII, IX, X. According to the 3 fold validation results, 2 set of 3 testing rates can achieve 98% detection rate, another one is around 92.66%. But we can clearly see artificial neural network has better classification in drowsiness detection.

TABLE VIII CONFUSION MATRIX OF NN CLASSIFICATION (1<sup>ST</sup> CROSS VALIDATION)

Accuracy: 98.44%		
Truth \ Prediction	Drowsy	Alert
	Drowsy	2514
Alert	707	9514

<b>Drowsy</b>	2466	70
<b>Alert</b>	117	9360

TABLE IX CONFUSION MATRIX OF NN CLASSIFICATION (2RD CROSS VALIDATION)

<b>Accuracy: 98.52%</b>		
<b>Truth \ Prediction</b>	<b>Drowsy</b>	<b>Alert</b>
<b>Drowsy</b>	2499	87
<b>Alert</b>	91	9385

TABLE X CONFUSION MATRIX OF NN CLASSIFICATION (3RD CROSS VALIDATION)

<b>Accuracy: 92.66%</b>		
<b>Truth \ Prediction</b>	<b>Drowsy</b>	<b>Alert</b>
<b>Drowsy</b>	1685	31
<b>Alert</b>	851	9446

#### E. Real time prediction based on neural network

The real time prediction model is based on neural network and to detect whether the driver is drowsy or not. 4 videos from 3 different drivers including 1 drowsy video 3 non-drowsy videos shown in TABLE III were used to train the model. The testing dataset contains two videos, one is drowsy the other is non-drowsy. One thing should be mentioned is that for the drowsy video claimed by the driver, our volunteers cannot make the decision whether the driver is drowsy or not by visually checking the video of face camera.

TABLE XI REAL TIME PREDICTION TESTING DATASET

Driver ID	Date	length	Fatigue or not
ID13	08/04/2014PM	32min	Not drowsy
ID0	02/19/2014	48 min	Driver claims drowsy

For the ID13 video, each segment is 30s with totally 63 segments. There are 53 segments out of 63 is predicted correct, which is non drowsy. 3 segments are low quality data, so it is questionable status, so the TNR is  $53/60 = 88.3\%$ .

But for the ID0 video, from driver's self-evaluation questionnaire, the driver claims the drowsy status as *relatively drowsy*, but our volunteers did not observed clear drowsy period from face video. There are 97 segments in total in this video, 26 are predicted as drowsy, and 31 segments are predicted as not drowsy. Due to the video quality, 40 segments are questionable result. Thus, the TPR of ID0 is 26.8%, which is pretty low.

The low TPR for ID0 may due to the following reasons: 1) The video quality is quite bad. 40 out of 97 segments are questionable due to the quality issue (too much sunshine). So the TRW's simulator cannot generate reliable detection of the lateral distance. 2) The drive experienced an early drowsiness state. However, the driver can still keep the vehicle very well. Therefore, there is no obvious clue of lane derivation.

#### F. Discussion

In our experiments, only the highway data (with the same lane widths) was used, because the lateral distance is sensitive to the lane width. Different highways and local road may have different widths. So, if the training and testing data come from roads with different widths, the proposed scheme may have high detection errors. And, in real application, it is very import to filter out the outliers due to normal turning, merge, exit, entry, etc. Another challenge is the how to design robust computer vision algorithm to detect the lane-related signals, especially for low quality video recorded at night or under bad weather condition. According to the experimental results, TRW's simulator can generate accurate signals if the video quality is sufficiently high. And lateral distance is a good candidate signal for drowsiness detection.

#### V. CONCLUSION AND FUTURE WORK

In this study, computer vision based feature with real world driving data were used to detect drowsiness. There is a huge potential use of this study in terms of driving safety or driving behavior analysis. We implement the data mining technique and also compared the classification methods, not only focus on the time domain but also applied frequency domain wavelet decomposition vector features to solve the problem.

However, in the lack of sufficient drowsiness data in real world driving, comprehensive experiments is not always available. The initial experimental results illustrate that the proposed method has very good performance on detection of the drowsiness. In order to detect the early state of drowsiness, physiological signals may be integrated. Further work includes collecting more drowsiness data of real word driving and improving the performance of the proposed method by incorporating more signals and features.

#### ACKNOWLEDGMENT

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