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Evaluation of a Smart Algorithm for Commercial Vehicle Driver Drowsiness Detection

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***Abstract*— Drowsiness is a safety hazard in commercial vehicle driving. The conditions to which truck drivers are exposed put them at higher risk as compared to passenger car drivers. Unobtrusive drowsiness detection methods can avoid catastrophic crashes by warning or assisting the drivers. This paper describes an experimental analysis of commercially licensed drivers who were subjected to drowsiness conditions in a truck driving simulator and evaluates the performance of a neural network based algorithm which monitors only the drivers' steering input. Correlations are found between the change in steering and the state of drowsiness. The results show steering signals differences can be used effectively for detection.**

I. Introduction

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. The Fatality Analysis Reporting System (FARS) indicates 1,544 fatalities due to driver drowsiness, per year. 3,300 of drowsiness related accidents (including 84 fatalities) involved drivers of combination unit trucks. A U.S. National Transportation Safety Board (NTSB) study in 1990 indicates that fatigue is the most frequent contributor to fatal crashes. Drowsiness accounts for 1% to 3% of all U.S. motor vehicle crashes [1]. In 15% of single vehicle fatal truck crashes, fatigue was believed to be involved [2]. Based on NHTSA General Estimates System (GES) statistics [3], although the frequency of drowsiness related crashes involving passenger vehicle is greater than that of trucks, due to high exposure level of trucks the number of involvement per vehicle life cycle for trucks is about 4 times greater. Crashes that involve a driver falling asleep are on average very serious in terms of injury severity and property damage [4], [5]. It has been shown by researchers that subjects can not predict when they will have a serious sleep attack [6]. Long-haul truck drivers get less sleep than is required to be alert on their job [7]. In another study, researchers showed in spite of the knowledge of factors influencing the risk of becoming drowsy, the drivers tend to continue driving [8].

Long hours of continuous wakefulness, irregular driving schedules, night shifts, sleep disruption or fragmented sleep due to split off-duty time put truck drivers more at risk [9], [10], [11].

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Driver drowsiness detection technologies may have the ability to avoid a catastrophic accident by warning the driver of his/her drowsiness.

Some researchers use physical and physiological data of drivers to measure or detect drowsiness. These include the measurement of brain wave or EEG [12], and eye activity. PERCLOS (PERcent eyelid CLOSure) is one of the most widely accepted measures in scientific literature for measurement and detection of drowsiness [13], [14].

There are numerous valuable studies on the effect of driver's inattention and drowsiness on driving performance for truck driver using field data [15], [16]. Because of the risks of involving the drivers in dangerous drowsy scenarios, some researchers tend to perform the experiments in a simulated environment [17]-[21].

Researches indicate variables related to vehicle lane position show good correlation with drowsiness [22], [23], [17].

Reference [24] suggests that there exists some correlation between micro steering movements and drop in vigilance. Reference [25] reported that steering wheel reversals and standard deviation of steering wheel angle are two measures that show some potential as drowsiness indicators.

Reference [26] developed a driver drowsiness detection system at the Toyota Motor Company. The authors used steering adjustment time to estimate drowsiness.

According to reference [27] phase plots of steering wheel angle verses steering wheel velocity can be used as an indicator of drowsiness.

A system that relies solely on steering inputs provides a number of benefits over the more common means of detecting drowsiness through eye-tracking or lane departure detection systems. A steering-only detection system is unobtrusive, capable of being implemented inexpensively with a minimal amount of additional sensors and computing power, and immune to problems associated with the dependency of other detection systems to the environment and weather such as performance degradation under low-light or rainy conditions.

Center for Intelligent Systems Research (CISR) previously developed an algorithm, which is based on Artificial Neural Network (ANN) learning of driver steering [19]-[21]. They trained an ANN model using data from a car driving simulator, driven by human subjects under various levels of sleep deprivation. However, it was not clear whether this system would also work for drowsiness detection in large commercial vehicles. Significant differences include the additional experience and training of truck drivers, the dynamics of the trucks versus cars, and the different feel of the steering systems in trucks and cars. Consequently, altered driver behavior and steering signals might limit the effectiveness of this approach for trucks tractor trailers.

New experiments were conducted with commercially licensed truck drivers as subjects in the truck driving simulator. This paper presents the results of these experiments and shows some new findings in steering behavior which is critical before vehicles encounter a crash or hazardous situations. Based on both previous findings and the new results, it develops the design of a drowsiness detection method for commercial trucks using Artificial Neural Network (ANN) classifier, trained and tested in a simulated environment. Success of the detection method from the truck simulator results is also compared with the previous results from the passenger car experiment.

II. Experiment

Experiments were conducted at the Center for Intelligent Systems Research (CISR) Truck Driving Simulator Laboratory (TDSL) [28]. TDSL is fixed base driving simulator, and organized around a real full size truck cabin. CISR TDSL includes:

1) Sophisticated vehicle dynamics and traffic models
2) Superior quality graphics
3) A five channel projection systems with a 135 degrees front field-of-view and two side view mirrors
4) A fully instrumented truck cabin with all original displays, controls, and pedals
5) An electronic gear box system with 8 forward gear ratios
6) An advanced steering feedback system using a controller and a DC motor to generate realistic truck steering feel
7) A head-mounted eye closure measuring system

Four infrared digital cameras recording driver's face, hands, and feet motions and projected driving scene during simulation.

The actual data of a 52-mile section of Interstate 70 (form Topeka to Junction City, Kansas) was used to design the simulator scenario. The scenario was developed in a way to induce monotony and drowsiness. The posted speed limit was 105 km h^{-1} (65 mph). The traffic vehicles could intelligently adjust their speed and lane to keep a safe distance with the surrounding vehicles. The designed traffic volume in the driver's traveling direction was low and had minimum effect on drivers' behavior.

Thirteen truck drivers (subjects), with valid commercial driving license, ranging in age from 23 to 60 years (mean age=41 years) completed the experiments. Each driver had to complete two driving sessions, a morning session and a night session. Prior to each test, each participant completed a practice session to get familiar to the simulator environment.

The night before morning session, the subjects were asked to have at least 8 hours of sleep. For the morning session, they drove the simulator for one full length of the scenario (52 miles). After completing the morning session, the subjects followed their normal life activity. They were instructed to have limited amount of caffeine and no sleep during that day.

At the same night, each subject drove the same 52 miles of simulated driving scenario repeatedly between 1:30 to 5:00 AM for the night session. The drivers were susceptible to doze off and fall sleep since they were sleep deprived.

During each experiment drivers' inputs, vehicle kinematics, traffic information, eye data and digital video of drivers' face were recorded for data analysis and labeling.

III. Assessment of Drowsiness

The drowsiness of the tested drivers was identified in two ways. A description of each follows.

A. *Subjective Drowsiness Rating (SDR)*

The driver behavior, performance and eye closure were observed during testing and off-line observation of video data. All behavioral signs indicating a state of drowsiness were subjectively observed and recorded. The subjective assessment of drowsiness was conducted on a five-level rating scale from 0 to 4:

-- SDR 0: alert.
-- SDR 1: questionable.
-- SDR 2: moderately drowsy.
-- SDR 3: very drowsy (doze-off).
-- SDR 4: extremely drowsy (asleep).

Although SDR is a subjective variable to demonstrate the level of drowsiness, it cannot correctly represent the severity of the drowsiness. For this purpose, another variable was defined as Severity of Drowsiness (SEVD), measured as the total time while SDR$\geq$ 3 divided by the driving time.

B. *Eye Closure Measure (PERCLOS)*

PERCLOS quantifies the percentage of time the eye is more than 80 % closed. This measure indicates the intervals of time when the eyes were closed.

The eye tracking data was gathered as an additional verification and is not part of the proposed detection method.

However, the eye tracking system experienced some difficulties either during calibration or measurements, for a few subjects with facial features like glasses with reflections or excessive head movements, etc. This resulted in false recordings. Alternatively, the subjective method was especially useful for identifying driver drowsiness. This relied on observation data from live recording and subsequent independent video analysis.

For average 0.75 hours morning session driving, the average SDR was 0.15, while for average 2.13 hours night session driving, the average SDR was 2.25. Average PERCLOS was 7% for morning sessions and 22% for night sessions. SDR and PERCLOS showed a significant difference between day and night sessions (SDR: F=134.27, P<0.001, Eye: F=12.61, P=0.002).

Fig 1 shows average SEVD and PERCLOS for each driver during morning and night sessions. The figure illustrates higher values of the severity of drowsiness and PERCLOS for night sessions. The night values also vary from subject to subject.

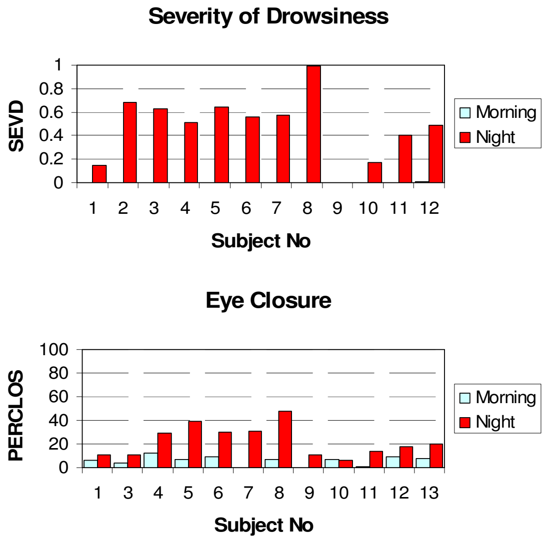

Fig. 1. Average SEVD and PERCLOS for morning and night sessions. (Night session video data for subject 13 and PERCLOS data for subject 2 and morning sessions of subject 7 and 9 had error during recording.)

IV. Data analysis

A. *Effect of Sleep Deprivation on Driving Performance*

The data from the experiments was analyzed to identify the potential variables that had good correlation with drowsiness. The goal of the data analysis was also to check whether similar degradation characteristics could be observed for the new truck experiment. The degradation characteristics of steering control parameters were analyzed in detail. The statistical analysis showed that steering wheel angle and lateral displacement had significant correlation with the level of drowsiness. There was also a drastic correlation between number of crashes and drowsiness. According to the data, drowsiness was the cause of most of the crashes during night sessions. Two types of crashes were observed: run-off-road and collision with other vehicles. Ninety-one percent of the night drowsiness related crashes were the result of run-off road incidents.

B. *Effect of Drowsiness on Steering Behavior*

According to the analysis of the steering data, drowsiness affected the steering behavior in two consecutive phases. In the first phase, called impaired phase or phase-I, the driver was not able to smoothly control the truck. The steering corrections in this phase were large (large amplitude), resulting in large amplitude maneuver in vehicle trajectory (zigzag driving). The phenomenon was supported by the previous car experiment [19]-[21] and other researcher [24].

In the next phase, the dozing off phase (phase-II), the driver had no feedback or corrective action on the steering angle. The phenomenon could be recognized by flatten steering signal (constant values) over a short period of time combined with increasing lateral displacement. Fig 2 displays a sample of the described signs of driving performance degradation in the lateral position and steering data for about one minute before a run-off road crash caused by drowsiness. Review of data for all crashes from 10 subjects reflects a similar two phase steering behavior. Fig 3 shows each subject's steering behavior for 5000m driving distance before the first crash. The night steering wheel data are compared with the corresponding morning data at the same driving distance.

The two-phase steering behavior is a significant finding for the development of a smart detection system which is based on steering signal prior to a hazardous situation or a crash eminent condition. The detection timing, period for averaging the steering signal, and the magnitude of the signal are all critical factors. Missing the two-phase phenomena could lead to unsuccessful detection.

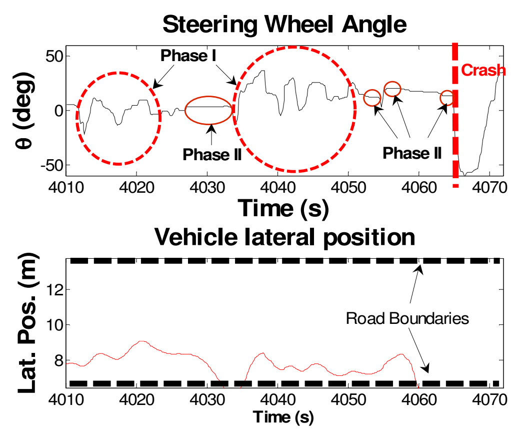

Fig. 2. Steering behavior degradation before a run-off road crash for one sample subject.

V. Method

An Artificial Neural Network is trained to learn steering input of commercial truck drivers under different driving states (alert and drowsy). This system is used to detect truck driver drowsiness based on steering activity. The training of the neural network was based on the learning of the phase-I steering performance degradation. The data of the experiment on truck drivers in a simulated environment was used to train and test the ANN. Prior to training the network, the effect of road curvature on steering wheel angle was removed. This filtered steering data were also preprocessed

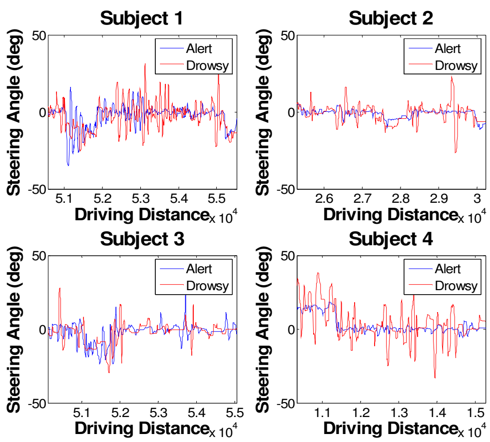

Fig. 3. Steering wheel angle signal before crash.

and coded into a vector to be applied as input into the network. The sum of vectors on every 15-second interval was used as the ANN input. Two separate sets of preprocessed vectors were used to train and test the neural network. Fig 4 shows a schematic of the detection model. Based on the input vector, the ANN output is in a coded vector format, representing alert or drowsy state.

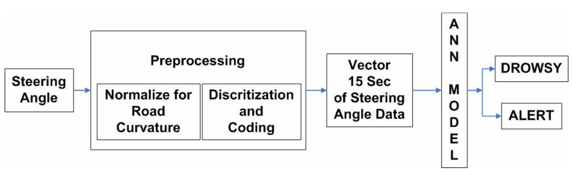

Fig. 4. Schematics of the ANN method.

A. *Data Preprocessing*

To train and test the network, the data from the steering angle was preprocessed and converted into a 1 by 8 vector state, representing 15 seconds of steering activity before being presented to the ANN model.

The data was preprocessed in two steps before presenting to the ANN. In the first step, the effect of road curvature was eliminated. In the second step, the data was discretized to allow a vector state presentation of the steering angle.

B. *Elimination of the Road Curvature on Steering Angle*

Road horizontal geometry normally includes two types of geometric sections, straight lines and curves. In the straight sections, the steering angle signal consists of only the steering adjustments for lane keeping. In the curve sections, including clothoids which connect straight and curve segments, the steering signal contains the waveform for lane keeping as well as the waveform for negotiating road curvature. The effect of curvature can be removed from steering wheel angle signal by subtracting the signal trend from the original signal. A simplified and modified procedure of trend extraction was used. In this method, if four or more consecutive data points were of the same sign (positive for right turn and negative is for left turn) and their sum were greater than or equal to 15 (absolute) degrees, then all these points were assumed to be from a curve or portion of a curve section. The mean value of these data points was then subtracted from each of these points (Fig.5).

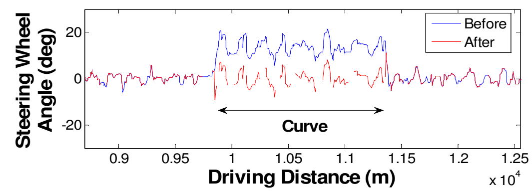

Fig. 5. Steering wheel data before and after road curvature removal.

1) *Input/Output Discretization*

For the input of the ANN, the steering signal was discretized and coded into a one by eight vector. The steering angle amplitude is divided into 8 smaller ranges, r_1 to r_k. These ranges are defined as follows:

$$-\sum_{k=i}^{4} p_k > r_i \ge -\sum_{k=i-1}^{4} p_k ; i=\{1,2,3,4\} \quad (1)$$

$$\sum_{k=9-i}^{4} p_k \le r_i < \sum_{k=8-i}^{4} p_k ; i=\{5,6,7,8\} \quad (2)$$

where p_k are constant. By choosing different values for p_k, the coded vector can be calibrated for different driving behaviors. Some drivers make small and accurate steering correction (low amplitude) while others are less sensitive to their lane keeping and make larger steering movement (higher amplitude) in their normal driving behavior. Larger values for p_k are used for drivers with large steering movement to make discretization ranges wider. p_0 and p_4 represent upper and lower steering angle limits respectively ($p_0=90^0$ and $p_4=0$). Over a given period of time, T, if the mean steering value fell into one of the ranges represented by r_i, the i^{th} component of the eight-dimensional vector state, $I(T)$, was set to 1. The other indices values are equal to zero. For this study T is one second.

After vectorizing the mean steering for each second, each vector was summed over an interval of n point resulting ANN input vector $X(n)$:

$$X(n) = I(T) + I(2T) + \ldots + I(nT) \quad (3)$$

For $n=15$, $X(n)$ represents 15 seconds of steering activity.

During the supervised training of the neural network, the input vectors, $X(n)$, were classified into two output vectors. Vector [1,0] represents alert state and vector [0,1] demonstrates drowsy state.

C. *Artificial Neural Network*

The neural network architecture is a three-layer, feed forward network as shown in Fig 6. The error-propagation supervised learning algorithm was used to update the weights.

600 exemplars from 8 subjects were used for training the network. To avoid memorizing the data during the training algorithm, a set of 200 exemplars were used for cross

validation. This is a supervised training in which the known input-output patterns are presented to the network and the ANN learns (stores) the information. The input patterns are the exemplars, i.e. 15-second summed of discretized steering

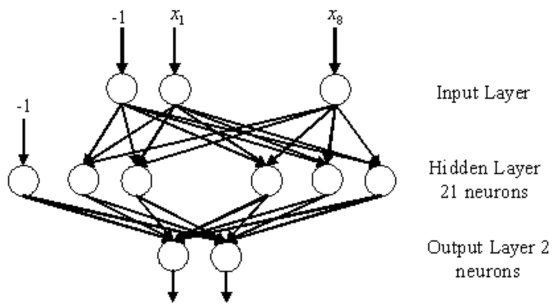

Fig. 6. Neural network architecture.

angle, and the output is known state of the driver, i.e. the desired output vector, $D(n)$. $D(n)$ is represented by a classifying vector value of [1,0] for awake and [0,1] for sleep. Therefore, for training, for each input example X corresponds to a known output $D(n)$. The presentation of input-output patterns (i.e. $X \rightarrow D(n)$) is random, selected from the 600 exemplars. Training an ANN requires selecting the right and optimum architecture for the various training parameters. The ANN training was performed multiple times with varying parameters until the best results were obtained. The tangent hyperbolic activation function, with output range from –1 to 1, was applied to neurons of the hidden and

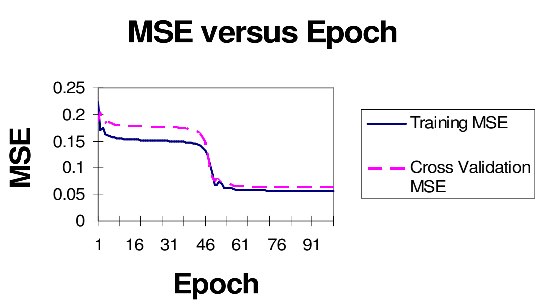

Fig. 7. ANN training performance.

the output layers. Fig 7 shows Mean Square Error (MSE) for training and cross validation of the network. These graphs indicate the network performance during training. The cross validation error always stayed below the training error showing the network generalization. The smooth drop of MSE indicates that the ANN performed very well.

VI. Model Testing and Results

During the training process, the ANN was tested to evaluate its performance. The design of the algorithm was based on detection of steering behavior in phase-I. The testing set of drowsy state was from the periods when the steering behavior was erratic (large steering) and the severity of drowsiness (SEVD) was greater or equal to 0.5. The data from the morning sessions were used to generate the testing set of alert state. Table I shows network testing performance for the best network weights. The test data set contained 600 input vectors (each vector representing 15 seconds of driving). The test data was not used in training or cross validation, in other words, the network had never seen this data before.

TABLE I
ANN MODEL RESULTS

OUTPUT/ DESIRED	AWAKE	DROWSY
WAKE	288	40
DROWSY	37	235
% CORRECT	89	85

The network correctly identified 235 out of a total of 275 phase-I drowsy intervals, i.e. an accuracy of 85 %. There were 37 out of 325 (11%) "false alarms", intervals that were in the "awake" class but were misclassified as "drowsy". Also, 40 out of 275 (14%) intervals that were in the drowsy class were misclassified by the network as "awake". Fig 8 shows the ANN model results for two sample subjects during entire morning and night sessions. The model results are also compared to eye and SEVD. The SEVD plots are eliminated for the morning sessions since the drivers were alert during morning. In the figure the abscissa represents 15 seconds time intervals. For the ANN output, each red bar means the ANN is classifying that particular interval as

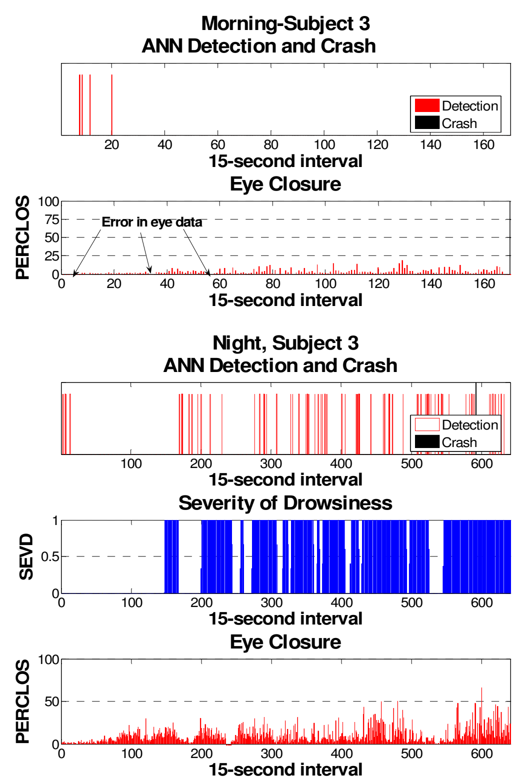

Fig. 8. ANN model results for a sample subjects during entire morning and night sessions.

"drowsy" while the rest are classified as "awake". In Fig 8, these crashes are shown by a black line.

To further investigate the system detection performance, the five minutes preceding the crashes of each driver was observed and analyzed. The studied crashes had at least 5 minutes time difference. The observation is summarized in Table II. (In the table the term "warning" is a hypothetical one, synonymous with the detection.)

TABLE II
OBSERVATION OF STEERING DATA 5 MIN (15S X 20) BEFORE A CRASH

Subject No.	No. of observed Crashes	Average time of the nearest warning (min)	Average time of the farthest (first) warning (min)	Average No. of ANN detections	Average No. of 15-s periods in which phase-II behavior occurred
2	6	1.9	3	2.7	4.3
3	3	1	0.5	3.5	5
4	3	0.6	4.9	9.3	12
5	4	0.4	4.9	7.5	9.5
6	3	1.9	4.5	5	7.7
7	4	1.6	4.0	3	8.2
8	3	2.1	3.5	3.3	11.7
11	5	0.8	4.2	8	2.6
12	6	2.4	3.4	2.3	9
13	13	1	2.5	2.5	1
Average		**1.4**	**3.5**	**4.7**	**7.1**

An evaluation of the ANN model shows good performance under the crash prediction metric. The system issued at least one detection for 97% of all the observed crashes experienced by any of the subjects. On average, 4.8 detections were issued during the five minute preceding the crash. The first detection was issued on average 3 minutes and 52 seconds prior to the crash. The final detection was issued on average 1 minute and 30 seconds before the crash. The table also shows that there are numerous doze off events (phase-II) in which no detection was issued. As explained, phase-II steering behavior is characterized by a period with no steering correction. Therefore, the ANN algorithm cannot detect these events since it was trained for phase-I events when the steering signal amplitude is large. Fig 9 shows ANN detection output versus steering and lateral displacement signals 5 minutes before a selected crash. To have better comparison with lateral displacement data, the illustrated steering data in the figure were before preprocessing.

VII. Discussion and Conclusion

A method for detecting truck driver drowsiness based on ANN is examined in a truck driving simulator. The performance of the drowsy driver detection systems for truck drivers was acceptable and similar to previous systems [19]-[21] that detected drowsiness in passenger car drivers. The truck driver fatigue detection systems performed extremely well in the most important evaluation metric – timely crash prediction. A comparison of the two studies

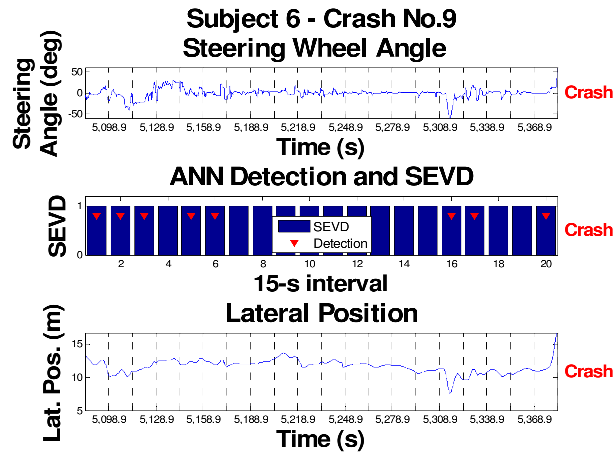

Fig. 9. Sample of missed detections because of phase-II steering behavior.

shows that the results are very similar. The two experimental conditions were not the same and differed in the type of simulator and driver (subject) population, although the amount of sleep deprivation were the same. Table III shows the results for both of these studies. The percentage accuracy during training decreased slightly for the truck study. The number of false alarms decreased slightly for the truck study.

TABLE III
COMPARISON OF RESULTS OF TWO STUDIES (CAR VS TRUCK DRIVING)

	Truck Study	Car Study
False Alarms	11 %	13%
Accuracy	85%	86%
First Crash Prediction	100%	100%

Based on the accuracy and the crash prediction results, the detection system holds the promise of safer roadways when coupled with a warning system.

References

[1] J. M. Lyznicki, T. C. Doege, D. R. M, and W. M. A, "Sleepiness, driving, and motor vehicle crashes," *Journal of American Medical Associates*, vol. 279, pp. 1908-1913, 1998.

[2] J. S. Wang and R. R. Knipling, "Single Vehicle Roadway Departure Crashes: Problem Size Assessment and Statistical Description," US Department of Transportation, National Highway Traffic Safety Administration, WAshington D.C. 1994.

[3] R. R. Knipling and W. W. Wierwille, "Vehicle-based drowsy driver detection: current status and future prospects," presented at IVHS America Fourth Annual Meeting, 1994.

[4] A. L. Pack, A. M. Pack, E. Rodgman, A. Cucchiara, D. F. Dinges, and C. W. Schwab, "Characteristics of Crashes Attributed to the Driver Having Fallen Asleep," *Journal of Accident*

Analysis and Prevention, vol. 27, pp. 769-775, 1995.

[5] J. S. Wang and R. R. Knipling, "Backing crashes: Problem size assessment and statistical description," NHTSA, Washington D.C. 1994.

[6] C. D. Wylie, T. Shultz, J. C. Miller, and M. M. Mitler, "Commercial Motor Vehicle Driver Fatigue and Alertness Study, Project Report," Federal Highway Administration, Washingotn D.C. 1996.

[7] M. Mitler, J. Miller, J. Lipsitz, K. Walsh, and C. Wylie, "The sleep of long-haul truck drivers," *New England Journal of Medicine*, vol. 337, pp. 755–761, 1997.

[8] S. Nordbakke and F. Sagberg, "Sleepy at the wheel: Knowledge, symptoms and behavior among car drivers," *Journal of Transportation Research Part F*, vol. 20, pp. 1-10, 2006.

[9] P. Gander and I. James, "Investigating Fatigue in Truck Crashes," presented at Road Safety Research, Policing, Education Conference, Wellington, New Zealand, 1998.

[10] P. Hamelin, "Lorry driver's time habits in work and their involvement in traffic accidents," *Ergonomics*, vol. 30, pp. 1323-33, 1987.

[11] A. McCartt, J. Rohrbaugh, M. Hammer, and S. Fuller, "Factors associated with falling asleep at the wheel among long-distance truck drivers," *Journal of Accident Analysis and Prevention*, vol. 32, pp. 493-504, 2000.

[12] T. Akerstedt and M. Gillberg, "Subjective and Objective Sleepiness in the Active Individual," *International Journal of Neuroscience*, vol. 52, pp. 29-37, 1990.

[13] R. Grace, V. E. Byrne, D. M. Bierman, J. M. Legrand, D. Gricourt, R. K. Davis, J. J. Staszewski, and B. Carnahan, "A drowsy driver detection system for heavy vehicle," presented at Proceedings of the 17th Digital Avionics Systems Conference, 1998.

[14] D. F. Dinges, M. Mallis, G. Maislin, and J. W. Powell, "Evaluation of techniques for ocular measurement as an index of fatigue and as the basis for alertness management," National Highway Traffic Safety Administration 1998.

[15] L. C. Barr, C. Y. D. Yang, R. J. Hanowski, and R. Olson, "Assessment of driver fatigue, distraction, and performance in a naturalistic setting," *Journal of the Transportation Research Board*, vol. 1937, pp. 51-60, 2005.

[16] S. G. Klauer, T. A. Dingus, V. L. Neale, and R. J. Carroll, "The effect of fatigue on driver performance for single and team long-haul truck drivers," presented at Proceeding of the International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design, 2003.

[17] T. Pilutti and G. Ulsoy, "Identification of driver state for lane-keeping tasks: Experimental results," presented at The American Control Conference, Albuquerque, NM, 1997.

[18] M. Gillberg, G. Kecklund, and T. Åkerstedt, "Sleepness and performance of professional drivers in a truck simulator - comparisons between day and night driving," *ournal of Sleep Research*, vol. 5, pp. 12-15, 1996.

[19] R. Sayed and A. Eskandarian, "Unobtrusive drowsiness detection by neural network learning of driver steering," *In: Proceedings of the Institution of Mechanical Engineers. Part D, Journal of Automobile Engineering*, vol. 215, pp. 969-975, 2001.

[20] R. Sayed, A. Eskandarian, and M. Oskard, "Driver drowsiness detection using Artificial Neural Networks," presented at Transportation Research Board 80th Annual Meeting, Washington D.C., 2001.

[21] R. Sayed, A. Eskandarian, and M. Oskard, "Monitoring drowsy drivers with Artificial Neural Network," presented at In Proceedings of 11th Intelligent Transportation Society of America Conference, 2001.

[22] J. H. Skipper, W. Wierwille, and L. Hardee, "An investigation of low level stimulus induced measures of driver drowsiness," Virginia Polytechnic Institute and State University IEOR, Blacksburg, Virginia 1984.

[23] T. A. Dingus, L. Hardee, and W. W. Wierwille, "Development of Impaired Driver Detection Measures," Department of Industrial Engineering and Operations Research, Virginia Polytechnic Institute and State University, Blacksburg, VA, USA Departmental Report 8504, 1985.

[24] D. Chaput, C. Petit, S. Planque, and C. Tarrière, "Un système embarqué de détection de l'hypovigilance," *Journées d'études: le maintien de la vigilance dans les Transports,Lyon, France*, 1990.

[25] M. Elling and P. Sherman, "Evaluation of Steering Wheel Measures for Drowsy Drivers," presented at 27th ISATA, Aachen, Germany, 1994.

[26] J. Fukuda, E. Akutsu, and K. Aoki, "Estimation of driver's drowsiness level using interval of steering adjustment for lane keeping," *JSAE Review, Society of Automotive Engineers of Japan*, vol. 16, pp. 197-199, 1995.

[27] G. P. Siegmund, D. J. King, and D. K. Mumford, "Correlation of steering behavior with heavy-truck driver fatigue," *SAE Special Publications*, vol. 1190, pp. 17-38, 1996.

[28] A. Eskandarian, R. Sayed, P. Delaigue, J. Blum, and A. Mortazavi, "Advanced driver fatigue research," Federal Motor Carrier Safety Administration 2006.