Real-Time Detection and Classification of Driver Distraction Using Lateral Control Performance

Joonwoo Son
Convergence Research Center for Future Automotive Technology
Daegu Gyeongbuk Institute of Sci. & Tech. (DGIST)
Daegu, Republic of Korea
json@dgist.ac.kr

Myoungouk Park
Convergence Research Center for Future Automotive Technology
Daegu Gyeongbuk Institute of Sci. & Tech. (DGIST)
Daegu, Republic of Korea
violet1211@dgist.ac.kr

***Abstract*— This paper suggests a real-time method for detecting both visual and cognitive distraction using lateral control performance measures including standard deviation of lane position (SDLP) and steering wheel reversal rate (SRR). The proposed method adopts neural networks to construct detection models. Data for training and testing the models were collected in a driving simulator in which fifteen participants drove through a highway. They were asked to complete either visual tasks or cognitive tasks while driving to create distracted driving periods. As a result, the best performing model could detect distraction with an average accuracy of 93.1%.**

Keywords-driver distraction; distraction classsification; driving performance; machine learning; neural network.

I. INTRODUCTION

Recent technological advances have enabled a wide variety of information systems to be integrated into a vehicle in order to increase safety, productivity, and comfort. However, drivers are also exposed to more distraction sources than before [1]. The driver's distraction is a specific type of inattention that occurs when drivers divert their attention away from the driving task to focus on another activity instead [2]. The major types of in-vehicle distraction can be categorized into visual-manual and cognitive distraction.

There have been efforts to monitoring driver's distraction in real time using driving performance [3], eye movement measures [4][5], and physiological measures [6]. However, most previous studies have focused on a specific distraction type, either visual or cognitive.

Thus, this paper presents results using neural networks for detecting and classifying visual and cognitive driver's distractions trained using lateral control performance measures, including the Standard Deviation of Lane Position (SDLP) and Steering wheel Reversal Rate (SRR).

II. DISTRACTION CLASSIFICATION MODEL

As shown in Figure 1, lateral performance measures including SDLP and SRR have different profiles according the type of distraction. Based on this behavioral difference, the distraction detection and classification model was constructed.

A. *Experimental Setup for Learning Data Collection*

The experiment was conducted in the DGIST fixed-based driving simulator, which incorporated STISIM Drive™ software and a fixed car cab. The virtual roadway was displayed on a wall-mounted. Sensory feedback to the driver was also provided through auditory and kinetic channels. Distance, speed, steering, throttle, and braking inputs were captured at a nominal sampling rate of 30 Hz.

B. *Generation of distraction*

In this study, visual distraction was generated by an arrow search task, which only required visual processing demand and minimal cognitive processing [7]. The arrow search task had three different arrangements of arrows to create three levels of difficulty. Cognitive distraction at three distinct levels was created using an auditory delayed digit recall task, so called n-back task. The n-back task requires participants to repeat the nth stimulus back in a sequence [8].

C. *Experimental Procedure*

Fifteen young males, in the 25-35 age range (M=27.9, SD=3.13), were recruited to collect visually and cognitively distracted driving data. Following informed consent and completion of a pre-experimental questionnaire, participants received 10 minutes of adaptation time in a simulator. The simulation was then stopped and participants were trained in the n-back task while remaining seated in the vehicle. When the simulation was resumed, participants drove on a straight highway twice, one for visual distraction and the other for cognitive. Each driving takes about 20 minutes, and participants perform a secondary task, i.e., n-back task or arrow task at a specified segment.

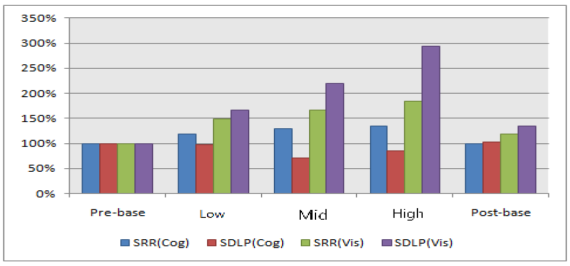

Figure 1. Comparison of lateral control performance

D. Input Features

The SDLP and the SRR were used for detecting both types of distraction in the classification models. The SRR was calculated by counting the number of steering wheel reversal from the low pass filtered steering wheel angle per minute. For cognitive distraction, the selected cut-off frequency of the low pass filter was 2Hz and the gap size of the reversal angles was 0.1 degree. For visual distraction, the cut-off frequency and the gap size were 0.6Hz and 3 degrees. The SDLP in both distraction types was calculated from 0.1Hz high pass filtered lateral position based on the AIDE report [9].

E. Model Training and Testing

Radial Basis Probabilistic Neural Networks (RBPNN), which are known as one of suitable methods for classification problems [10], were used to construct the driver's distraction classification model. For training and testing the distraction detection models, the simulated driving data sets were used. Each data set consists of a driving only period and three levels of distracted driving periods. Each task duration was divided into multiple segments based on a time window size. This study considered seven window sizes, i.e., 2, 3, 5, 10, 15, 20 and 30 seconds. Among the segments in each task, half of them were used for training and the others for testing.

III. Result And Discussion

The performance of the distraction detection models varies depending on the window sizes. As shown in Table 1, the time windows between 3 and 10 seconds provided good performance in overall. Under the visual distraction, the highest accuracy was 98.5% with 10 seconds window, but the model performance was degraded when the window sizes are smaller than 3 seconds or bigger than 15 seconds. In the cognitive distraction, the best accuracy was 93.6% with 2 seconds window.

In general, the SRR represents the control effort needed to cope with time sharing induced by a secondary task, and thus provides a direct measure of the consequences of visual or cognitive demand on lateral control. Thus, the increased SRR could be interpreted in terms of increased workload. Regarding the SDLP, the increased SDLP is often observed under visual distraction, but cognitive distraction causes the reduced SDLP [11]. Due to the characteristics of lateral performance measure, the classification performance in visual distraction could have specific regions of window size to provide better accuracy rate.

TABLE I. Model Performance With Different Window Sizes

Size (sec.)	Total Accuracy	Cognitive Accuracy				Visual Accuracy			
		Low	*Mid*	*High*	*Avg.*	*Low*	*Mid*	*High*	*Avg.*
2	86.4	91.6	94.9	94.2	93.6	83.3	79.1	75.3	79.3
3	90.0	83.7	86.7	88.7	86.3	96.0	93.3	91.7	93.7
5	93.1	86.7	90.0	94.4	90.4	97.8	96.1	93.3	95.7
10	92.8	80.0	88.9	92.2	87.0	100.0	96.7	98.9	98.5
15	85.8	90.0	88.3	100.0	92.8	71.7	80.0	85.0	78.9
20	83.7	80.0	77.8	95.6	84.4	75.6	84.4	88.9	83.0
30	81.7	73.3	80.0	83.3	78.9	83.3	86.7	83.3	84.4

IV. Conclusion

In this paper, we proposed a real-time method for detecting both types of driver's distraction using the lateral control performance measures including SDLP and SRR. In order to collect training and testing data, fifteen participants drove in a driving simulator and completed three different levels of cognitive and visual tasks. The distraction detection and classification was performed by RBPNN models.

The results show that the proposed models were able to detect both types of driving distraction with high accuracy. The model performance was assessed with the cross-validation scheme. As a result, the highest accuracy rate in overall model performance was 93.1%. And it is also expected that the accuracy can be improved by applying more sophisticated algorithms and supplementary inputs.

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