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DETECTION OF COGNITIVE AND VISUAL DISTRACTION USING RADIAL BASIS PROBABILISTIC NEURAL NETWORKS

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ABSTRACT−This paper suggests a real-time method for detecting a driver's cognitive and visual distraction using lateral driving performance measures. The algorithm adopts radial basis probabilistic neural networks (RBPNNs) to construct classification models. In this study, combinations of two driving performance data measures, including the standard deviation of lane position (SDLP) and steering wheel reversal rate (SRR), were considered as measures of distraction. Data for training and testing the RBPNN models were collected under simulated conditions in which fifteen participants drove on a highway. While driving, they were asked to complete auditory recall tasks or arrow search tasks to create cognitively or visually distracted driving periods. As a result, the best performing model could detect distraction with an average accuracy of 78.0 %, which is a relatively high accuracy in the human factors domain. The results demonstrated that the RBPNN model using SDLP and SRR could be an effective distraction detector with easy-to-obtain and inexpensive inputs.

KEY WORDS : Distraction, Driving performance, Cognitive distraction, Visual distraction, Neural networks

1. INTRODUCTION

Recent technological advances have enabled a wide variety of information systems to be integrated into vehicles to increase safety, productivity, and comfort. However, improperly deployed technology can increase driver distraction and, consequently, degrade safety (Son *et al*., 2011a). It is also known that today's drivers are exposed to more sources of distraction than ever before (Donmez and Liu, 2015). Driver 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 (Ranney, 2008). The sources of these distractions can be electronic, such as navigation systems and smart phones, or more traditional activities, such as interacting with passengers and eating. These distracting tasks can affect drivers in different ways and can be categorized into visual, manual, and cognitive distractions.

Among these distraction types, manual distraction can be detected directly by monitoring in-vehicle control input activities such as adjusting the volume up or down, and turning the radio on or off. Visual distraction, which occurs when drivers look away from the roadway, is straightforward to measure as well; it can be reasonably observed by the duration and frequency of glances away from the road. Unlike manual and visual workload, cognitive workload is difficult to measure directly because it is essentially internal to the driver. Thus, there have been efforts to monitor driver distraction using subjective measures, physiological measures (Healey and Picard, 2005; Son *et al*., 2011b), eye movement measures (Bergasa *et al*., 2006; Liang *et al*., 2007), and driving performance measures (Son *et al*., 2011a; Son and Park, 2011; Zhang *et al*., 2004). Among these measures, it is known that driving performance measures can detect cognitive or visual distraction by using simple, inexpensive methods through readily available in-vehicle information (Son and Park, 2011; Zhang *et al*., 2004). However, because driving performance measures reveal different patterns according to the type of distraction, i.e., cognitive or visual distraction, different measures and distraction detection algorithms should be applied for different types of distractions.

This paper suggests a simple neural network algorithm for detecting both types of driver distraction using lateral driving performance measures, including the standard deviation of lane position (SDLP) and steering wheel reversal rate (SRR). The results demonstrate that a combination of lateral driving performance measures, such as SDLP and SRR, can be effectively used as the inputs to a distraction detector that can distinguish cognitive and visual distraction at a high accuracy rate.

2. MEASURES AND MODELS FOR CLASSIFYING DISTRACTION TYPES

2.1. Driving Performance Measures

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Previous studies have shown that distraction undermines driving performance by disrupting the allocation of visual attention to the driving scene, and the processing of attended information (Liang *et al*., 2007). Consequently, distraction leads to significantly degraded lateral controllability and increased response times to sudden obstacles. In this study, therefore, lateral controllability was used as a driving performance measure under distraction. More specifically, lateral position variation and steering wheel activity were selected to assess lateral controllability.

2.1.1. Lateral position variation

Lateral position variation is one of the most commonly used driving behavior metrics. Increased or reduced variation in lateral position when engaged with visual or cognitive tasks could be interpreted as a symptom of driver overload and an increased risk of incorrect decisions. Lateral position variation can be calculated as the standard deviation of lateral position (SDLP). In this study, a high pass filter with a 0.1 Hz cut-off frequency is applied to lane position data to reduce data length dependence (Östlund *et al*., 2004).

2.1.2. Steering wheel activity

Visual or cognitive distraction yields increased steering activity during a driving task. The effect of visual distraction on steering behavior is straightforward to interpret. That is, visual time-sharing induced by surveillance tasks or non-driving related tasks interferes with basic tracking control by intermittently reducing the visual tracking input. During glances away from the road, tracking errors build up, and steering wheel movements for correction increase (Östlund *et al*., 2004).

The relationship between cognitive load and steering performance is somewhat vague. It is known that the metric is sensitive to cognitively demanding tasks, despite the lack of clear scientific interpretation. Under secondary cognitive tasks, the increase is mainly in smaller steering wheel movements, the majority of which are smaller than one degree of rotation.

From the literature, the SRR can be used for measuring the increase in visual or cognitive distraction. It is defined as the number of steering wheel reversals larger than a certain minimum angular value (gap size) during a certain period, i.e., a time window. Two versions of the reversal rate metric were proposed in the previous study (Östlund *et al*., 2004), defined in terms of the parameter setting below:

- Large Reversals: Gap size = 3°,
  LPF cut-off = 0.6 Hz
- Small Reversals: Gap size = 0.1°,
  LPF cut-off = 2 Hz

2.2. Detection of Distraction

In this study, two major types of driver distraction will be considered, as follows:

- Visual distraction: Tasks that require the driver to look away from the roadway to visually obtain information;
- Cognitive distraction: Tasks that are defined as mental workload, which involves thinking about something other than the driving task.

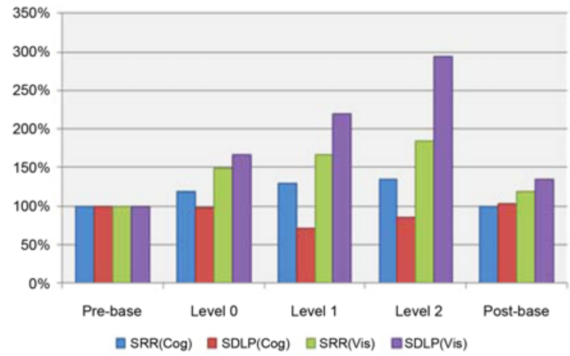

Figure 1. Comparison of steering performance.

The best method to distinguish between visual and cognitive distraction is by watching eye movements. However, this method requires an additional camera-based sensing system and a complex image processing algorithm. In this study, a simple classification method using driving performance is proposed.

According to preliminary analysis, we find that SRR measures increase as both visual and cognitive distractions are increased, but SDLP measures move in different directions according to the type of distraction, as shown in Figure 1. From the differences in the lateral control patterns, we can infer the type of distraction, i.e., visual or cognitive.

2.3. Neural Network Models for Detecting Distraction

Radial basis probabilistic neural networks (RBPNNs) were used to construct a driver distraction classification model using lateral driving performance measures. The RBPNN model combines the benefits of radial basis functional neural networks (RBFNNs) and probabilistic neural networks (PNNs). The RBFNN has the advantage of good generalization ability, good tolerance to input noise, and online learning ability (Yu *et al*., 2011). The advantage of PNN is that training is easy and instantaneous (Ahmadlou and Adeli, 2010). In the RBPNN models, the first layer computes distances from the input vector to the training input vectors and produces a vector whose elements indicate how close the input is to a training input. The second layer sums these contributions for each class of inputs to produce a vector of probabilities as its output. Finally, a complete transfer function on the output of the second layer picks the maximum of these probabilities and produces a 1 for that class and 0 for the other classes.

3. MODEL CONSTRUCTION

3.1. Data Source

3.1.1. Experimental setup

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 2.5 m by 2.5 m wall-mounted screen at a resolution of 1024 × 768 pixels. 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.

A display was installed on the screen beside the rear-view mirror to provide information about the elapsed time and the distance remaining in the drive.

3.1.2. Participants

Participants were required to meet the following criteria: aged between 25 and 35 years, drives on average more than twice a week, in self-reported good health and free from major medical conditions, not taking medications for psychiatric disorders, scores 25 or higher on the Mini-Mental State Examination (Folstein *et al*., 1975) to establish reasonable cognitive capacity and situational awareness, and has not previously participated in a simulated driving study. The sample consisted of 15 males who were in the 25 to 35 age range (M = 27.9 years, SD = 3.13 years).

3.1.3. Visual distraction

The arrow search task, which required visual processing and only minimal cognitive processing, was selected as a surrogate task for visual distraction (Engström *et al*., 2005). To create three levels of difficulty for the arrow task, i.e., level 0 (easy), level 1 (moderate), and level 2 (hard), twelve different arrangements of arrows for each level, presented in a series of two-minute trials, were pre-designed. Example screenshots of the three difficulty levels are shown in Figure 2. There is an upward-pointing target arrow in 7 out of the 12 pictures, and on the others there is not. If participants touched the YES or NO buttons, which were located on left side of the arrow matrix on the touch screen, the arrows disappeared immediately. When participants did not respond within a 10-second period, the arrows were discarded, the trial was scored as a miss, and new arrows appeared.

3.1.4. Cognitive distraction

An auditory delayed digit recall task was used to create periods of cognitive demand at three distinct levels. This form of n-back task requires participants to repeat out loud the nth stimulus in a sequence presented via audio recording (Mehler *et al*., 2011). The lowest level n-back task is the 0-back, where the participant is to immediately repeat out loud the last item presented. At the moderate level (1-back), the next-to-last stimulus is to be repeated. At the most difficult level (2-back), the second-to-the-last stimulus is to be repeated. The n-back was administered as a series of 30 s trials consisting of 10 single digit numbers (0-9) presented in randomized order at an inter-stimulus interval of 2.1 s. Each task period consisted of a set of 4 trials at a defined level of difficulty, resulting in demand periods that were each 2 min long.

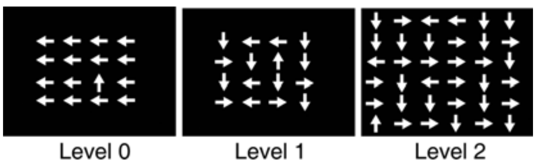

Figure 2. Three levels of difficulty for the arrow task.

3.1.5. Procedure

Following informed consent and completion of a pre-experimental questionnaire, participants received 10 min of driving practice and adaptation time in the simulator.

The simulation was then stopped and participants were trained on the n-back task while remaining seated in the vehicle. N-back training continued until participants met the minimum performance criteria. Performance on the n-back was subsequently assessed at each of the 3 demand levels with 2 min breaks between each level. When the simulation was resumed, participants drove in good weather through 37 km of straight highway twice, once for the visual distraction condition, and once for cognitive distraction. Each driving experiment took about 20 min, and participants performed a secondary task, i.e., the n-back task or arrow task, during specified segments.

The order in which secondary tasks were presented was balanced, so that half of the participants drove under a cognitive workload first. Figure 3 shows the main experimental procedure for the cognitive and visual

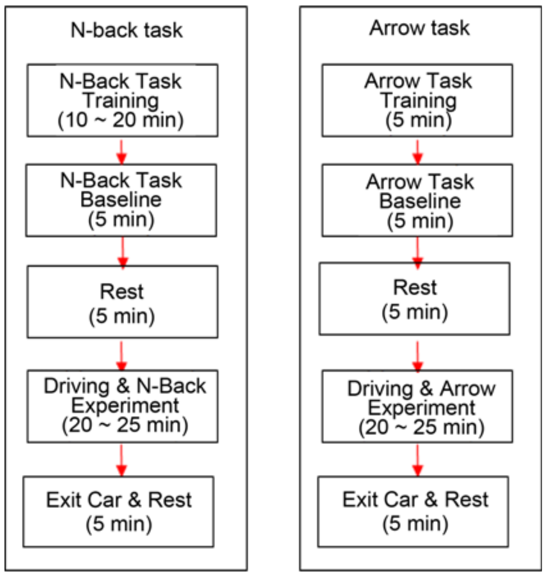

Figure 3. Main experiment flow.

workload tasks. In the main driving experiments, minutes 5 through 7 were used as a single-task driving reference (baseline). Each secondary task (n-back or arrow search) period was 2 min in duration (four 30 s trials). A 2 min rest and recovery period were provided before presenting instructions for the next task. The presentation order of the three levels of task difficulty was randomized across participants.

3.2. Model Characteristics and Training

3.2.1. Definition of distraction type

The type of distraction was classified into two categories, i.e., visual or cognitive, based on the secondary tasks. The distracted period during the n-back task was defined as cognitive distraction, and during the arrow search task as visual distraction in this model. Each surrogate task had three levels of difficulty, as mentioned previously.

3.2.2. Input features

Two driving performance measures, SDLP and SRR, were considered as input features to classify the type of driver distraction in the RBPNN models. SRR was calculated by counting the number of steering wheel reversals per minute from the low-pass-filtered steering wheel angle data. For cognitive distraction, the selected cut-off frequency of the low-pass filter was 2 Hz, and the gap size of the reversal angles was 0.1°. For visual distraction, the cut-off frequency and the gap size were 0.6 Hz and 3°. SDLP in both distraction types was calculated from the 0.1 Hz high-pass-filtered lateral position data with lane changes removed.

3.2.3. Summarizing parameters

In this study, window size was considered the summarizing parameter for the inputs. Window size denotes the period over which driving performance measures were averaged. Comparisons by window size identified the appropriate length of data that could be summarized to reduce noise in the input data without losing useful information. This study considered seven window sizes: 2, 3, 5, 10, 15, 20, and 30 s.

3.2.4. Model training and testing

RBPNNs were used to construct the driver distraction detection models. In this study, the models were trained using the NEWPNN function in MATLAB. For training and testing RBPNN models, visual or cognitive distraction driving data were used. Each dataset consisted of data collected under single-task (driving only condition) and three levels of dual-task (n-back task or arrow search task) conditions. One task period was divided into multiple segments based on the seven kinds of window sizes. For example, if the model used a 30-s window, one task period, i.e., 120 s, was divided into four segments as shown in Figure 4. In each task, half of the segments, i.e., two segments per subject in a 30-s window, were used for training and the other segments were used for testing. Thus, each neural net was trained and tested using different sets of measurements, i.e., 480 instances in total for training and testing (15 subjects × 8 tasks × 4 segments per task) with 30-s windows. The 2-s window case had the biggest datasets, i.e., 7200 instances in total for training and testing. Because the detection model is evaluated on the data disjointly from the training data, the performance evaluated using the cross-validation scheme correctly reflects the actual generalization capability of the derived model (Zhang *et al*., 2004). Model performance was evaluated with testing accuracy, which is the ratio of the number of instances correctly classified by the model to the total number of instances in the testing set.

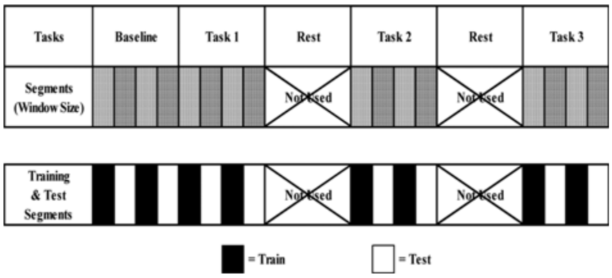

Figure 4. Allocation of segments to training and testing sets.

4. RESULTS AND DISCUSSION

To quantify the performance of the RBPNN models, accuracy, sensitivity (true positive rate), and miss rate (false negative rate) were calculated according to the following equations:

$$Accuracy = \frac{TP + TN}{TP+TN+FP+FN} \tag{1}$$

$$Sensitivity = \frac{TP}{TP+FN} \tag{2}$$

$$FN\_Rate = \frac{FN}{FN+TP} \tag{3}$$

where TP is true positive, TN is true negative, FP is false positive, and FN is false negative.

The accuracy of the distraction detection models varied with window size. As shown in Table 1, time windows larger than 5 s provided good performance overall. Under the visually distracted condition, the highest classification accuracy was 78.3 % for the 20 s window, which showed statistical significance compared with the 2 s and 3 s window sizes (see Table 1). However, the accuracy degraded as the window sizes became smaller. For cognitive distraction, the best classification accuracy was 79.7 % for the 15 s window, which showed statistically significant better results compared with most of the other sizes.

Table 1. Model performance with different window sizes.

Time window	Avg. Acc.	Cognitive distraction			Visual distraction		
		Acc.	Sens.	FN rate	Acc.	Sens.	FN rate
2 s	70.6	75.0**	93.6	6.4	66.1**	79.3	20.7
3 s	73.5	75.1**	86.3	13.7	71.8*	93.7	6.3
5 s	74.5	75.9**	90.4	9.6	73.1	95.7	4.3
10 s	74.9	75.8	87.0	13.0	74.0	98.5	1.5
15 s	78.0	79.7	92.8	7.2	76.3	78.9	21.1
20 s	78.3	71.8*	84.4	15.6	78.3	83.0	17.0
30 s	77.5	72.1*	78.9	21.1	77.5	84.4	15.6

** $p < .01$, * $p < .05$

Although there was no clear trend among different window sizes, the classification models that used window sizes between 2 and 15 s showed better accuracy. For visual distraction, SRR represents the steering control effort needed to cope with visual time sharing induced by a secondary task, and thus provides a direct measure of the consequences of visual demand on lateral control. In this case, SRR is directly related to visual distraction, and increased SRR could be interpreted in terms of increased risk. On the other hand, increased SDLP is often an effect of visual distraction. Owing to the characteristics of lateral performance measures, the classification performance in visual distraction could have specific regions of window size that provide a better accuracy rate.

It can be speculated that time windows greater than 5 s are best for acquiring useful information about visual distraction.

For cognitive distraction, SRR is sensitive to cognitive loading tasks as well, but the relation between cognitive load and steering performance is still not entirely understood. Thus, model accuracies for different window sizes in cognitive distraction show no trend. However, when the window size is less than 15 s, the accuracy rate is higher than 75 %.

5. CONCLUSION

In this paper, we proposed a method for detecting a driver's cognitive and visual distraction using lateral driving performance measures, including SDLP and SRR. To train and test the neural network models, driving data were collected from simulated highway driving. The participants were asked to complete three different levels of auditory recall tasks or arrow search tasks while driving in a simulator. The distraction detector was developed using RBPNN models that were implemented using the MATLAB NEWPNN function.

The results show that the proposed RBPNN models could detect both types of driving distraction with high accuracy. Model performance was assessed with the cross-validation scheme, which is widely accepted by the machine learning community. As a result, the highest type classification accuracy rate in overall model performance was 78.0 %, which is a relatively high accuracy in the human factors domain. It is also expected that accuracy could be improved by applying more sophisticated algorithms and supplementary inputs.

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REFERENCES

Ahmadlou, M. and Adeli, H. (2010). Enhanced probabilistic neural network with local decision circles: A robust classifier. *Integrated Computer-Aided Engineering* **17**, **3**, 197–210.

Bergasa, L. M., Nuevo, J., Sotelo, M., Barea, R. and Lopez, M. E. (2006). Real-time system for monitoring driver vigilance. *IEEE Trans. Intelligent Transportation Systems* **7**, **1**, 63–77.

Donmez, B. and Liu, Z. (2015). Associations of distraction involvement and age with driver injury severities. *J. Safety Research*, **52**, 23–28.

Engström, J., Johansson, E. and Östlund, J. (2005). Effects of visual and cognitive load in real and simulated motorway driving. *Transportation Research Part F: Traffic Psychology and Behaviour* **8**, **2**, 97–120.

Folstein, M. F., Folstein, S. E. and McHugh, P. R. (1975). Mini-mental state: A practical method for grading the cognitive state of patients for the clinician. *J. Psychiatric Research* **12**, **3**, 189–198.

Healey, J. and Picard, R. W. (2005). Detecting stress during realworld driving tasks using physiological sensors. *IEEE Trans. Intelligent Transportation Systems* **6**, **2**, 156–166.

Ranney, T. A. (2008). Driver Distraction: A Review of the Current State-of-knowledge. National Highway Traffic Safety Administration, Washington, DC. No. DOT HS 810 704.

Liang, Y., Reyes, M. L. and Lee, J. D. (2007). Real-time detection of driver cognitive distraction using support vector machines. *IEEE Trans. Intelligent Transportation Systems* **8**, **2**, 340–350.

Mehler, B., Reimer, B. and Dusek, J. A. (2011). MIT AgeLab Delayed Digit Recall Task (n-back). Massachusetts Institute of Technology, Cambridge, Massachusetts, USA.

Östlund, J., Peters, B., Thorslund, B., Engström, J., Markkula, G., Keinath, A., Horst, D., Juch, S., Mattes, S.

and Foehl, U. (2004). Driving Performance Assessment-methods and Metrics. Information Society Technologies. No. IST-1-507674-IP. 118−129.

Son, J., Lee, Y. and Kim, M. (2011a). Impact of traffic environment and cognitive workload on older drivers' behavior in simulated driving. *Int. J. Precision Engineering and Manufacturing* **12**, **1**, 135−141.

Son, J., Mehler, B., Lee, T., Park, Y., Coughlim, J. and Reimer, B. (2011b). Impact of cognitive workload on physiological arousal and performance in younger and older drivers. *Proc. 6th Int. Driving Symp. Human Factors in Driver Assessment (DA2011)*, University of Iowa, Iowa City, Iowa, USA, 87−94.

Son, J. and Park, S. W. (2011). Cognitive workload estimation through lateral driving performance. *SAE Paper No*. 2011-28-0039.

Yu, H., Xie, T., Paszczynski, S. and Wilamowski, B. M. (2011). Advantages of radial basis function networks for dynamic system design. *IEEE Trans. Industrial Electronics* **58**, **12**, 5438−5450.

Zhang, Y., Owechko, Y. and Zhang, J. (2004). Driver cognitive workload estimation: A data-driven perspective. *Proc. IEEE 7th Int. Conf. Intelligent Transportation Systems*, Washington, USA, 642−647.