Identification of Driver Cognitive Workload Using Support Vector Machines with Driving Performance, Physiology and Eye Movement in a Driving Simulator

Joonwoo Son[1,#], Hosang Oh[1], and Myoungouk Park[1]

1 DGIST HumanLab, 50-1 Sang-Ri, Hyeonpung-Myeon, Dalseong-Gun, Daegu, South Korea, 711-873
Corresponding Author / E-mail: json@dgist.ac.kr, TEL: +82-53-785-4740, FAX: +82-53-785-4759

KEYWORDS: Driver state estimation, Cognitive workload, Support vector machines, Intelligent vehicle, Driving simulator

This paper suggests experimental approaches for identifying driver's cognitive workload using support vector machines (SVMs) with driving performance, physiological response and eye movement data. In order to construct a classification model for detecting high cognitive workload condition, driving simulation experiments were conducted. For the experiments, 30 participants (15 younger males in the 25-35 age range (M = 27.9, SD = 3.13) and 15 older males in the 60-69 (M = 63.2, SD = 1.74)) drove a simulated highway in a fixed-base driving simulator. While driving through 37 km of straight highway, participants conducted three levels of cognitive secondary tasks, i.e. an auditory delayed digit recall task, at specified segments for 10 minutes and their driving performance, physiological response and eye movement data were collected. In this study, the model performances with different combination of measures were assessed with the nested cross-validation method. As a result, it was demonstrated that the proposed SVM models were able to identify driver's cognitive workload with high accuracy. The best performance was achieved with a combination of the standard deviation of lane position (SDLP), physiology and gaze information. The best model obtained 89.0% accuracy, sensitivity of 86.4% and specificity of 91.7%.

1. Introduction

Driver inattention causes a significant problem for road traffic safety, because it degrades driving performance and situational awareness. According to car accident statistics, between 25% and 78% of crashes are caused by driver inattention.[1] Drivers' cognitive workload, when it is too low (e.g. fatigue or drowsiness) or too high (e.g. stress or multiple tasks), is related to driver inattention and accident.[2,3] Thus, a proper identification of a driver's workload and spare capacity is one of the promising approaches to designing an adaptive automotive user interface for reducing driver distraction.[4] By monitoring driver's workload, the adaptive interface can provide timely and targeted information when the driver has the spare capacity.

According to the final report of the Driver Workload Metric Project[5] in the United States, driver workload is defined as the competition in driver resources between the driving task and a concurrent subsidiary task, occurring over the task's duration, as manifested in degraded lane keeping, longitudinal control, object-and-event detection, or eye glance behavior. Two major types of driving workload are visual and cognitive workload. Visual demand is straightforward, but cognitive workload is difficult to measure directly because it is essentially internal to the driver.[6] Nevertheless, there have been efforts to measure cognitive workload using subjective measures,[7,8] physiological measures,[9-12] eye movement measures,[13,14] and driving performance measures.[10,14] Among those measures, driving performance measures can detect the cognitive workload using easy and less expensive methods through readily available in-vehicle information.[15,16] However, driving performance measures are known to have limitations compared to others due to their reflected small changes with respect to the cognitive workload changes.[6,11,15]

On the other hand, physiological measures have been proposed as useful metrics for assessing workload. Mehler et al. found that a near linear increase in heart rate and skin conductance appeared as the workload levels increase.[11] Then, Son et al.[17] demonstrated that the combination of performance and physiological data can be effectively used for estimating cognitive workload, but the data sets in their study were limited to younger drivers. The results may not be so clearer for older adults.

Recent researches[3,13,14] suggested that cognitive workload induced gaze constriction due to higher levels of workload, this affects the allocation of attention to regions of the peripheral visual field through changes in visual search orienting and monitoring surrounding objects. Using this finding, Son et al.[18] reported that the combination of driving performance and eye movements could be effectively used as inputs to an artificial neural network models for discriminating high cognitive load conditions from normal driving. Unfortunately, the accuracy rate in the overall model performance was limited, i.e. 85%, and only younger drivers' data sets were used. Another limitation of the previous studies[17,18] is that they applied regular cross-validation method without optimizing learning parameters.

Thus, this paper extends the previous studies by 1) applying an advanced machine-learning algorithm, i.e. support vector machines to improve overall accuracy rates of driver's cognitive distraction, 2) extending data sets by adding older drivers' data sets in addition to the younger drivers' sets to overcome the limitations from previous studies, and 3) employing a nested cross-validation method.

2. Classification Algorithms

A number of classification algorithms have been introduced in the last decade for detecting cognitive workload. These include support vector machines,[4] and radial basis probabilistic neural networks.[15,17,18] A recent comparative study of classification performance among probabilistic neural network, support vector machine (SVM) and logistic regression concluded the SVM showed the best accuracy.[19]

SVM (Support vector machine), which is a machine-learning technique based on statistical learning theory, has been used for pattern classification and inference of nonlinear relationships between variables.[20,21] Fig. 1 shows the basic principle of a SVM in 2D space. Binary-class training data $D = \{(x_i, y_i)\}^l_{i=1}$, where x_i is a vector containing multiple features, and y_i is a class indicator with value either -1 or 1, are illustrated as circles and dots in Fig. 1, respectively. SVM maps the input space to higher dimensional feature space and constructs a hyperplane, which separates class members from non-members via a function Φ. The hyperplane yields a nonlinear boundary in the input space. The function Φ is written in the form of a kernel function $K(x_i, x_j) = \Phi(x_i)^T \Phi(x_j)$ used in the SVM calculation. When data are not linearly separable in the feature space, the positive penalty parameter C allows for training error ε by specifying the cost of misclassified training instances.[22] A positive constant value, C, controls the trade-off between the separation margin and the number of training instances that lie on the wrong side of the hyperplane. If C is very small, an inappropriately large fraction of support vectors may be derived. In contrast, if C is very large the analysis may over-fit to the training data instances, which may yield a low level of generalization ability. The SVM method allows avoiding over-fitting by minimizing the upper bound of the generalization error[23] to produce more robust models than traditional learning methods, which only minimize training error.

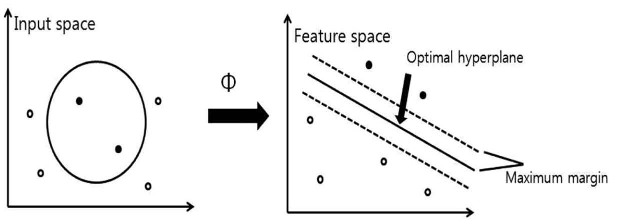

Fig. 1 The principles of SVM

3. Method

This section contains details of driving simulation experiments for collecting data sets, and method for constructing support vector machines model using the collected data.

3.1 Samples

In order to consider age differences, samples for collecting training and testing data were expanded to older drivers in this paper.[24,25] Thus, participants required to meet the following criteria: age within 25 to 35 or 60 to 69, driving frequency at least twice a week, self-reported good health condition and free from major medical conditions, not taking medications for psychiatric disorders, scored 27 or greater on the mini mental status exam[26] to screen cognitive impairment, and having not previously participated in a simulated driving study. The sample consisted of 30 males: 15 in the 25-35-age range (M = 27.9, SD = 3.13) and 15 in the 60-69 (M = 63.2, SD = 1.74).

3.2 Creation of cognitive workload

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 speak out loud the nth stimulus back in a sequence that is presented via audio recording.[11,14] 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-second trials consisting of 10 single digit numbers (0-9) presented in a randomized order at an inter-stimulus interval of 2.1 seconds. Each task period consisted of a set of four trials at a defined level of difficulty resulting in a series of demand periods that each lasts two minutes long.

Fig. 2 Fixed-based Driving Simulator

3.3 Experimental setup

The experiment was conducted in a fixed-based driving simulator, which incorporated STISIM Drive™ software and a fixed car cab (see Fig. 2). The virtual roadway was displayed on a 2.5 m by 2.5 m wall-mounted screen at a resolution of 1024 × 768. 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. Physiological and eye behavior data were collected using the MEDAC System/3 (NeuroDyne Medical Corp., Cambridge, MA) and the FaceLAB® 4.6 eye tracking system (Seeing Machines Ltd., Canberra, Australia), respectively. 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 driving experiment.

3.4 Procedure

As shown in Fig. 3, upon completion of informed consent and a pre-experimental questionnaire, participants spent 10 minutes of driving experience and adaptation time in the simulator. The simulation was then stopped and participants were trained in the n-back task while remaining seated in the vehicle. In order to minimize the influence of individual factors, n-back training continued until participants met minimum performance criteria, i.e. perfect in 0-back and more than 75% of correct answers in 1-back and 2-back tasks. Then each participant's baseline performance of n-back task was evaluated. Followed by 5 minutes rest, participants drove in good weather through 37 km of straight highway for 20 to 25 minutes. During the driving and n-back task experiment, minutes 5 through 7 were used as a single task driving reference (baseline). Thirty seconds later, 18 seconds of instructions introduced the task (0, 1 or 2-back). Each n-back period was 2 minutes in duration (four 30 second trials). A two-minute rest (recovery) period was provided before presenting instructions for the next task. Presentation order of the three levels of task difficulty was randomized across participants.

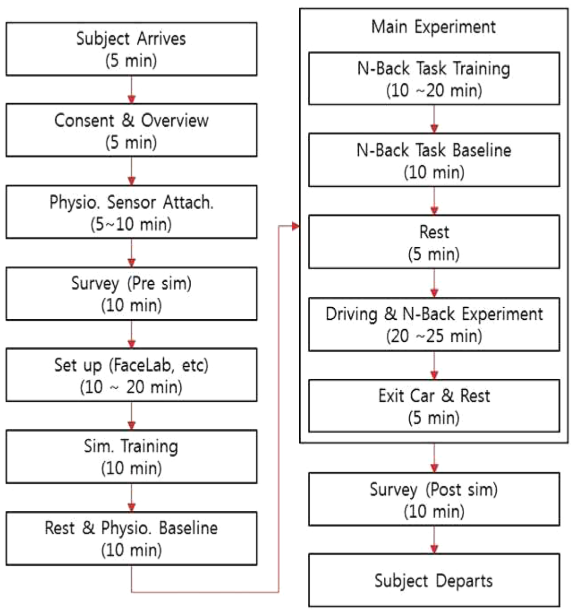

Fig. 3 Experimental Procedure

3.5 Definition of cognitive workload

The cognitive workload was classified into four categories based on the complexity of primary and secondary tasks. The secondary task, so called n-back task, has three levels of difficulty.[14] The 0-back task is a low-level cognitive challenge that is not particularly difficult and not intended to be significantly stressful. The 1-back condition requires an additional step up in cognitive load in that an individual must both correctly recall from short-term memory the item presented previously as well as entering and holding the new item in memory. It is expected that the 1-back would have moderate workload on individuals. The 2-back form of the task requires highest cognitive load to recall from short-term memory within the n-back task.

Although the cognitive workload was classified into four grades, i.e., driving only and driving with three levels of n-back task, the present study used two levels of cognitive workload, i.e. normal driving and high cognitive workload condition. Normal driving was defined as driving without any cognitive workload. The high cognitive workload condition was defined as the durations of driving while performing the most difficult cognitive task, the 2-back task.

3.6 Input features

Based on the study results of Son et al.,[15,17,18,27] Mehler et al.[11] and Reimer et al.,[14] six measures from three different domains were selected as input features to detect driver's cognitive workload in the SVM models. They were the standard deviation of lane position (SDLP) and steering wheel reversal rate (SRR) in the driving performance domain, heart rate (HR) and skin conductance level (SCL) in the physiological domain, and the standard deviation of horizontal gaze (SDHG) and the standard deviation of vertical gaze (SDVG) in eye behavior.

Each input data was calculated and filtered to remove outliers. The SDLP was calculated from 0.1 Hz high pass filtered lateral position data and lane changes were removed using the AIDE project guidelines.[28] The SRR was calculated by counting the number of steering wheel reversals that have more than 0.1 degree of reversal angle per minute from the 2 Hz low pass filtered steering wheel angle data.

The HR was converted from the Inter-beat Interval (IBI) that was calculated using the Librow's R-peaks detection algorithm (Librow^{TM}, Ukraine). The SCL was measured with a constant current configuration and non-polarizing, low-impedance gold-plated electrodes. Sensors were placed on the underside of the outer flange of the middle fingers of the non-dominant hand without gel.

In order to calculate the SDHG and the SDVG, raw gaze data were filtered with the following criteria as suggested by an earlier study:[14] 1) the FaceLAB's automated gaze quality index for the left and right eyes was categorized as optimal, 2) the x-axis position was between -1.5 m and +1.5 m, the y-axis position was between -1.0 m and +1.0 m, and 3) the data point was contained within a set of six valid measurements (approximately 100 ms).

3.7 Model training and cross-validation procedure

In this procedure, data that contained the driving only and data containing the 2-back task periods were summarized across the 10s-window without overlapping to form instances. Then, the segmented instances were normalized using z-score and labeled as ‘not distracted’ for normal driving condition or ‘cognitively distracted’ for high cognitive workload condition according to the distraction definitions.

In order to construct the SVM models, the Radial Basis Function (RBF) was chosen as the kernel function:

$$K(x_i, x_j) = e^{-\gamma|x_i - x_j|^2}$$

where x_i and x_j represent two data points, and γ is a predefined positive parameter. Using the RBF, we can implement both nonlinear and linear mapping by manipulating the values of γ and the penalty parameter C.[29,30] In the training procedure, the optimal values of C and γ were searched in the exponentially growing sequences ranging of 2^{-5} to 2^{15}. In this study, 360 instances (30 participants * 12 segments) were randomized and used for training and a cross-validation.

A nested cross-validation was adopted to train and evaluate the performance of the cognitive workload detection model. The nested cross-validation method allows the simultaneous optimal selection of parameters of SVMs and the unbiased estimation of the performance of the final SVM model. The detailed procedure of the nested cross-validation was described in Fig. 4 as a pseudo-code.[31]

The performances of SVMs were evaluated in three aspects, i.e., classification accuracy, sensitivity and specificity, using the following equations:[32]

```
Procedure Nested Cross Validation
1. Repeat N times:
   • Assign N-1 Subset to TrainingSet;
   • Assign remaining Subset to TestingSet;
  1.1 Repeat for i = 1, ..., m:
     1.1.1 Repeat N-1 times (only for the instances in the training set):
       - Assign N-2 Subsets to TrainingValidationSet;
       - Assign remaining Subset to TestingValidationSet;
       - Train the classifier on TrainingValidationSet using parameter αj;
       - Test it on TestingValidationSet.
    1.1.2 Record P(i), the average performance of the classifier
                                        over N-1 TestingValidationSets.
  1.2 Determine αj, where j=argmaxP(i) for i=1, ..., m;
  1.3 Train the classifier on the training set using parameter αj.
   • Test the classifier on the training set using parameter αj.
2. Return ρ, the average performance of classifier over N testing sets.
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Fig. 4 Pseudo-code of a nested cross-validation for performance estimation and model selection

$$Sensitivity = \frac{TP}{TP+FN} \times 100$$

$$Specificity = \frac{TN}{TN+FP} \times 100$$

$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP} \times 100$$

where, TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative (see Table 1)

4. Results and Discussion

4.1 Performance of the SVM Models

The performance of the SVM models was varied from 58.9% to 89.0% depending on the combinations of input features (see Table 1).

Among the SVM models with a single input feature, the heart rate (HR) showed the best accuracy. The HR-based model detected driver drive’s cognitive workload with 80.0% accuracy followed by the standard deviation of vertical gaze (SDVG) with 76.7%. The effectiveness of the HR to estimate a driver’s cognitive workload has often been reported by previous studies[10,11,27] and this result is consistent with the earlier findings. One of the authors’ previous studies using the radial basis probabilistic neural networks (RBPNNs) with younger driver’s physiological inputs[17] showed a slightly conflicted result, the RBPNN study[17] concluded that SCL was the best predictor of the cognitive workload. However, the performance of the SCL-based model in this study also showed a moderately high accuracy of 73.8%. The difference may be caused by the sample selection and the cross-validation method.

The SDVG-based SVM models also demonstrated promising performance with 76.7% accuracy. This accuracy is same as the author’s earlier study[18] using the RBPNNs with a 30 second window, but much higher than the results of the RBPNN with a 10 second window that is the same window size of this study. Although the SDVG showed better performance than the standard deviation of

Table 1 Confusion matrix representation

Actual State	Predicted State	
	High workload (Positive)	Normal driving (Negative)
High Workload	True Positive (TP)	False Negative (FN)
Normal Driving	False Positive (FP)	True Negative (TN)

Table 2 Classification accuracy of single and multiple input features

Input Feature	SDLP	SRR	SDHG	SDVG	HR	SCL	Driving	Gaze	Physio.	Gaze & Physio.	Driving & Physio.	Driving & Gaze
SDLP	58.9	75.0	73.8	76.8	79.0	76.7	-	80.8	84.2	**89.0**	-	-
SRR	-	71.7	79.2	78.9	81.0	79.2	-	82.5	82.6	88.6	-	-
SDHG	-	-	73.5	79.0	81.5	79.9	80.0	-	86.5	-	87.1	-
SDVG	-	-	-	***76.7***	82.6	81.1	78.1	-	86.1	-	87.4	-
HR	-	-	-	-	**80.0**	***82.9***	***80.7***	***86.1***	-	-	-	86.4
SCL	-	-	-	-	-	***73.8***	78.9	81.7	-	-	-	86.3
Driving	-	-	-	-	-	-	***75.0***	81.7	86.4	-	-	-
Gaze	-	-	-	-	-	-	-	***79.0***	88.1	-	-	-
Physio.	-	-	-	-	-	-	-	-	***82.9***	-	-	***88.8***

horizontal gaze (SDHG) in the eye movement domain, the difference is not significant and the result is not consistent with the previous studies. Reimer et al.[14] and Son et al.[27] have reported a statistically significant effect of cognitive workload has appeared in horizontal gaze concentration, but no significant effect in vertical gaze concentration. The results may have been affected by the driving simulator environment that was used in collecting the training and testing data. The driving simulator had one screen for the front-view and an additional display beside the rear-view mirror on the screen to provide time and distance information. In this particular driving simulator, a driver's horizontal gaze dispersion may be relatively small compared to real world driving due to the absence of side view and the additional display may increase a driver's vertical gaze movement. Therefore, the accuracy of the gaze-based SVM models needs to be validated with a field operational test data.

The best performance among the multiple input features was achieved by the combination of the physiology, gaze and SDLP. As shown in Table 3, the best combination model obtained 89.0% accuracy, sensitivity of 86.4% and specificity of 91.7%. The high specificity may reduce false alarms that may annoy to the drivers.

In general, all SVM models with physiological inputs, i.e., HR and SCL, obtained at least 82.6% accuracy. Especially, the HR played a key role in increasing increase the accuracy and specificity of the SVM models. The gaze features showed the next most promising performance with 79.0% accuracy. The all feature combination based SVM model was not optimal for the accuracy or specificity. This research suggested that an optimal model may be formed from the "best" combination of parameters rather than the inclusion of all potential parameters.

Table 3 Model performance(single feature & best combination)

Single Input						
Model	SDLP	SRR	SDHG	SDVG	HR	SCL
Sensitivity	62.5	67.2	82.8	71.9	77.8	75.0
Specificity	55.3	76.1	64.2	81.4	82.2	72.5
Accuracy	58.9	71.7	73.5	76.7	80.0	73.8
Best Combination						
Model	Physio. Gaze	Physio. Gaze SDLP	Physio. Gaze SRR	Physio. Driving SDHG	Physio. Driving SDVG	Physio. Driving Gaze
Sensitivity	85.0	86.4	86.7	83.6	85.0	87.5
Specificity	91.1	91.7	90.6	90.6	89.7	90.0
Accuracy	88.1	89.0	88.6	87.1	87.4	88.8

Table 4 Model performance with younger and older group

	Model	SDLP	SRR	SDHG	SDVG	HR	SCL
Younger	Sensitivity	73.4	76.6	81.3	66.7	79.2	78.1
	Specificity	52.1	75.5	65.1	70.8	87.5	78.1
	Accuracy	62.8	76.0	73.2	68.8	83.3	78.1
Older	Sensitivity	62.2	62.2	79.4	76.7	78.3	70.6
	Specificity	41.1	77.8	61.7	86.7	72.8	72.8
	Accuracy	51.7	70.0	70.6	81.7	75.6	71.7

4.2 Age Difference in Performance

It is important that the input features are not affected by age to implement the SVM models in a real world application. Thus, this study extended the data sets to older drivers and evaluated the performance difference of the SVM models between the younger and older group's data. According to the earlier studies,[11,14] the SRR, the SDVG and the SCL were significantly affected by age. As shown in Table 4, the SDVG showed the highest age difference in accuracy and specificity, and the largest difference in sensitivity was appeared in the SRR. In general, the results with younger drivers were better than older drivers in the driving performance domain, however this was reversed in the physiological domain. Interestingly, the performance of the SDHG and the SDVG differed across the age groups in the eye movement domain. The older group's performance with the SDVG was notably higher than their younger peers. From these differing results with respect to age in the physiology and gaze domains, it is recommended to use cross-domain measures for improving the overall robustness in the face of age factors.

5. Conclusions

In this paper, we proposed an algorithm for detecting driver's cognitive workload using driving performance, physiology and eye movement data. Two measures in each domain, i.e., the SDLP and the SRR for driving performance, the HR and the SCL for physiology and, the SDHG and the SDVH for eye movement, were considered as cognitive distraction indices. In order to collect driving data, participants drove on a highway in a driving simulator and were asked to complete three different levels of auditory recall tasks. Then, the driver's cognitive workload detection algorithm was constructed using the SVMs. The model performance was optimized and assessed through the nested cross-validation method. As a result, the proposed SVMs with the inputs of SDLP, Physiology (HR and SCL) and gaze (SDVG and SDHG) were able to detect the cognitive distraction with the highest accuracy of 89.0%.

It is recognized that this study has a limited data set in that the data was collected in a driving simulator with a straight highway road and a relatively homogenous traffic scenario. On- road data in a more diverse set of conditions is needed to fully assess the generality of the results.

ACKNOWLEDGEMENT

This research was supported in part by Daegu Gyeongbuk Institute of Science and Technology (DGIST) Research Program of the Ministry of Science, ICT and Future Planning (MSIP) (Project No. 13-S-01), and Establishment Program of Industrial Original Technological Base of the Ministry of Trade, Industry and Energy (MOTIE) (Project No. M0000009). This article represents a significant extension of work that appeared in part in the proceedings of the AVEC12.[18] The data sets in this article were used in part in the proceedings of the DA2011,[12] APAC-17,[15] and AutoUI 2011.[17]

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