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Development of Driver-State Estimation Algorithm Based on Hybrid Bayesian Network*

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***Abstract*—In this study, we develop and evaluate an estimation algorithm of abnormal driving states (drowsiness, distraction, and workload) based on a Hybrid Bayesian Network (HBN) using multimodal information. The HBN algorithm is expected to increase transportation safety by combining merits of both the Bayesian Network and clustering algorithm. In addition, multimodal data efficacy analysis through human-in-the-loop experiments is used to enhance the performance of the driver-state estimation algorithm. Performance results obtained the lowest false alarm rate and fastest calculation speed. The false alarm rate decreased from 18.2 to 15.5%, whereas the calculation speed decreased by 4.35%.**

I. INTRODUCTION

Extensive information and vehicle complexity have increased because of the development of sensors and vehicle technology. Combined with abnormal driving states such as drowsiness, distraction, and workload, the developments can cause fatal traffic accidents. Drowsiness during driving increases the risk of accidents that often result in driver injury or death [1]; distracted driving, that is, time spent by drivers with their eyes off the road, increases the risk of traffic accidents [2]. In addition, even if visual distraction does not occur while driving, cognitive workload such as talking on the phone is more likely to cause fatal traffic accidents [3].

II. DESIGN OF DRIVER-STATE ESTIMATION ALGORITHM

In previous studies, Liang [4–6] used the Hybrid Bayesian Network (HBN) to determine a driver's state of distraction, and she compared the performance of the Dynamic Bayesian Network (DBN) to that of the Support Vector Machine (SVM). If the Static Bayesian Network (SBN) contains many nodes, it performs at a slow calculation speed, which represents a disadvantage that HBN can remedy. HBN is a method that increases calculation speed by reducing the number of nodes that use clustering. In addition, Liang [4-6] integrated 19 variables into only three input variables, i.e., eye movement temporal and spatial measures, and driving performance measures. The results of her experiment show little difference in the accuracy of HBN, but the calculation speed was fastest [4-6].

Diverse sensing variables were used in previous studies. For example, PERCLOS (Percentage of Eye Closure), head nodding, blinking duration, frequency and interval were used in [7, 8] whereas PERCLOS and vehicle information such as lateral position and steering wheel information were used in other studies [i.e., 9] for estimating drowsiness. Eye blinking, face direction and PERCLOS were used [10,11] for driver distraction; and gaze direction, pupil diameter, head orientation, and heart rate were used [12] whereas only driving performance information were used [13] for estimating driver workload.

In this study, we adopt HBN to estimate a driver's state using information from image, voice, biometric, and vehicular modules. Multimodal sensory modules are expected to perform accurately and provide driver-state information even when some sensor parts malfunction. Furthermore, we performed human-in-the-loop experiments based on a driving simulator for the purpose of obtaining accurate variable clustering.

A. *Human-in-the-loop Experiments Based on Driving Simulator*

Two main experiments were performed based on the following driver states: drowsiness and distraction/workload. The drowsiness experiment was configured with a boring environment that causes the driver to feel drowsy. The independent variable of the drowsiness experiment was sleep time, and we divided the experiment participants into two groups. For one group, sleep time was restricted (4 h maximum). The other group was allowed to maintain proper sleep time (7 h minimum). The dependent variables were driver face data (e.g., blinking, PERcentage of eye CLOSure (PERCLOS), and head motion); voice data, such as conversation noise level; biometric data (e.g., heart rate); and vehicle data (e.g., velocity, longitudinal/lateral acceleration, gas/brake pedal input, steering-wheel angle, and angular velocity). The distraction/workload experiment consisted of a complex and noisy road environment that causes distraction and/or high workload. The independent variable for this experiment was a task performance in which the participants were asked to play music on their phones. In addition, the participants were requested to perform the N-back test while

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TABLE I. SELECTED VARIABLES BASED ON EFFICACY ANALYSIS

Module	Variables	Drowsiness	Distraction	Workload
Image	PERCLOS	0.002^{*}	-	-
	Blinking	0.018^{*}	-	0.050^{*}
	Head Motion	-	0.003^{*}	0.022^{*}
Voice	Conversation Level	0.020^{*}	0.039^{*}	0.036^{*}
Biometric	Heart Rate	0.000^{**}	0.074^{*}	0.011^{*}
Vehicle	Velocity	0.005^{**}	0.000^{*}	0.002^{*}
	Steering-wheel angle	0.028^{*}	0.005^{*}	0.033^{*}
	Gas pedal	0.029^{**}	0.030^{*}	0.019^{*}
	Brake pedal	-	0.000^{*}	0.001^{*}
	Longitudinal acceleration	-	0.001^{**}	0.001^{*}
	Lateral acceleration	0.040^{*}	0.001^{*}	0.001^{*}

Corresponding p-values are shown in parentheses. *Wilcoxon signed rank test, **Paired t-test

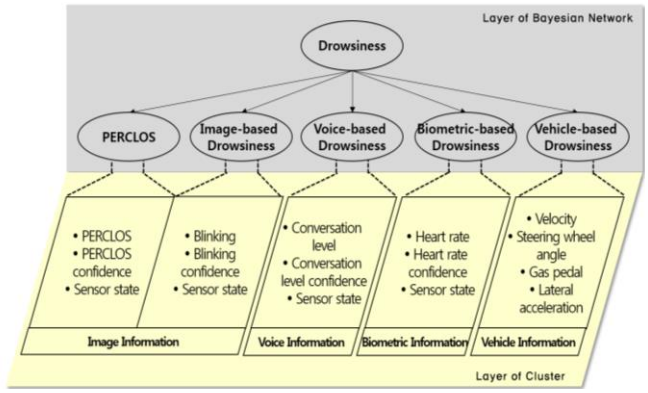

Fig. 1 HBN modeling for driver drowsiness states

answering a phone call [14]. The dependent variables were the same as those for the drowsiness experiment.

For the drowsiness experiment, we recruited four men with a mean age of 27 years with a standard deviation of 2.16 years. For the distraction/workload experiments, we recruited 15 men and 1 woman. The mean age of the men was 27.5 years with a standard deviation of 1.23 years. The woman's age was 26 years. All participants reviewed and signed an informed consent statement approved by the Internal Review Board (IRB) before beginning the experiment.

The drowsiness experiment was conducted in the following sequential order. Participants were trained (20 min), signed the experiment consent form (10 min), practiced driving (10 min), and finally performed main driving for the drowsiness experiment (50 min). The distraction/workload experiment was conducted in the following sequential order. Participants were trained (20 min), signed the experiment consent form (10 min), practiced driving (10 min), performed the main experiment for causing distraction/workload (10 min), and conducted baseline driving (10 min).

For the Hyundai Genesis coupe 2.0 automatic transmission vehicle as a medium-fidelity driving simulator. In addition, we collected vehicle information using SCANeR Studio 2 2.16 and a motion/dynamic/log computer of Innosimulation Inc.; image information regarding the driver using FaceLAB 4.6 version of Seeingmachine Inc.; voice information using a microphone of 3Can Inc. and MATLAB/SIMULINK of Mathworks Inc.; biometric information using BxM™BT™ of Zephyr Inc. Details of data collection and the pre-processing process of the integrated data are described in Yang and Jeong [15].

B. Analysis of Dependent Variables

Because of the small sample number (fewer than 30), we conducted a normality test prior to the efficacy analysis. The normality test was performed using the Anderson-Darling test at a significance level of 0.05. Typically, if data follow a normal distribution, the paired t-test, which is a parametric statistical analysis method, is performed at a significance level of 0.10. If data does not follow a normal distribution, the Wilcoxon signed-rank test, which is a nonparametric statistical analysis method, is performed at a significance level of 0.10.

As a result of efficacy analysis, we selected the following based on variables with statistical significance to estimate driver drowsiness: for the face, data such as PERCLOS and blinking; for voice, data such as conversation level; and for vehicle, data such as velocity, steering-wheel angle, gas pedal input, and lateral acceleration. In addition, we selected the following to estimate driver distraction: for the face, data such as head motion; for voice, data such as conversation level; for biometrics, data such as heart rate; and for vehicle, data such as velocity, steering-wheel angle, gas/brake pedal, and longitudinal/lateral acceleration. Finally, we selected the following to estimate driver workload: for the face, data such as blinking and head motion; for voice, data such as conversation level; for biometrics, data such as heart rate; and for vehicle, data such as velocity, steering-wheel angle, gas/brake pedal, and longitudinal/lateral acceleration. All of this information is summarized in Table I.

C. Hybrid Bayesian Network Modeling

Structure of Hybrid Bayesian Networks: HBN consists of two parts. The first part is a layer of cluster and the second is a layer of Bayesian network. Measured data from each module are classified into nodes of Bayesian network based on a clustering algorithm. Once clustered, the Bayesian network layer contains independent bipartite models consisting of parent (i.e., drowsiness, distraction, and workload) and child nodes (i.e., clustered variables).

Clustering of variables: We define PERCLOS, PERCLOS confidence, and a sensor state to a single child node to estimate the drowsiness state. The clustering of blinking, blinking confidence, and sensor state is defined as a child node of image-based drowsiness. The clustering of the conversation level, conversation-level confidence, and sensor state is defined as a child node of voice-based drowsiness. The clustering of the heart rate, heart-rate confidence, and sensor state is defined as a child node of biometrics-based drowsiness. The clustering of velocity, steering-wheel angle, gas pedal, and lateral acceleration is defined as a child node of vehicle-based drowsiness. HBN for drowsiness estimation

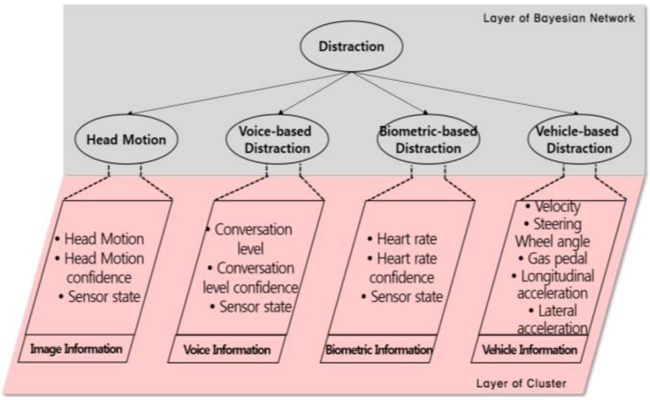

Fig. 2 HBN modeling for driver distraction states

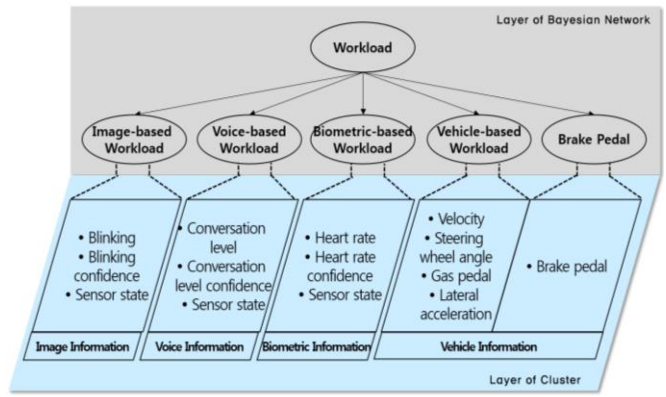

Fig. 3 HBN modeling for driver workload states

uses 19 variables and consists of one parent node and five child nodes. The HBN model for the estimation of drowsiness is shown in Fig. 1.

We define head motion, head-motion confidence, and sensor state to a single child node to estimate the distraction state. The clustering of the conversation level, conversation-level confidence, and sensor state is defined as a child node of voice-based distraction. The clustering of heart rate, heart-rate confidence, and sensor state is defined as a child node of biometrics-based distraction. The clustering of velocity, steering-wheel angle, gas/brake pedal, and longitudinal/lateral acceleration is defined as a child node of vehicle-based distraction. HBN for distraction estimation uses 19 variables and consists of one parent node and four child nodes. The HBN model for estimating distraction is expressed in Fig. 2.

We define the brake pedal input to a single child node to estimate the workload state. The clustering of blinking, blinking confidence, and sensor state is defined as a child node of image-based workload. The clustering of conversation level, conversation-level confidence, and sensor state is defined as a child node of voice-based workload. The clustering of heart rate, heart-rate confidence, and sensor state is defined as a child node of biometrics-based workload. The clustering of velocity, steering-wheel angle, gas pedal, and lateral acceleration is defined as a child node of vehicle-based workload. HBN for drowsiness estimation uses 19 variables and consists of one parent node and five child nodes. The HBN model for the estimation of workload is expressed in Fig. 3.

Generation of Conditional Probability Table: After setting up the model structure, we define the conditional probability table (CPT) for each node according to the causality shown in the HBN model. Conditional probability is defined by the following equation, i.e., the intersection probability of events A and B divided by the probability of event B:

$$P(A|B) = P(A \cap B) / P(B) \tag{1}$$

The parent node is defined as a binary node with either a true or false state. The child node is also defined as a binary node. Thus, the CPT has four combinations: 1) P(Child node true|Parent node true), 2) P(Child node false|Parent node true), 3) P(Child node true|Parent node false), 4) and P(Child node false|Parent node false). Each probability value is determined and tuned based on the experimental data.

After setting up the CPT, we also must choose an efficient inference algorithm to infer about driver states based on clustered variables. The inference algorithm in the Bayesian network is commonly divided into three types: symbolic, approximate, and exact. Markov random fields and expectation propagation are typical examples of approximate inference algorithms. The junction-tree algorithm, variable elimination, and clique-tree propagation are typical examples of exact-inference algorithms. We investigated the characteristics of the variable-elimination algorithm, a type of exact-inference algorithm. A variable-elimination algorithm can reduce iterative calculation using the distribution law. Thus, it has the advantage of reducing the algorithm's calculation speed [16]. Therefore, we selected the variable-elimination algorithm to reduce the calculation speed as compared to existing algorithms (e.g., junction-tree algorithm) when considering real-time. We implemented a driver-state estimation algorithm using the variable-elimination algorithm instead of using the MATLAB toolbox.

III. Performance Evaluation of Hybrid Bayesian Network

In order to evaluate the performance of the driver-state estimation algorithm, we compared three algorithms: 1) HBN when efficacy analysis is not used, 2) HBN when efficacy analysis is used, and 3) SBN. The drowsiness experiment compared the data from the sleep-restricted and adequate-sleep groups. The distraction/workload experiment compared the data from the experimental section in which distraction/workload is induced with a baseline. For the drowsiness experiment, we assumed that the participants in the sleep-restricted group were actually in a sleepy state. Furthermore, we assumed that the participants in the adequate-sleep group were awake. For the distraction/workload experiment, we assumed that the participants performed a distracted/workload activity during the section in which distraction/workload is induced. The

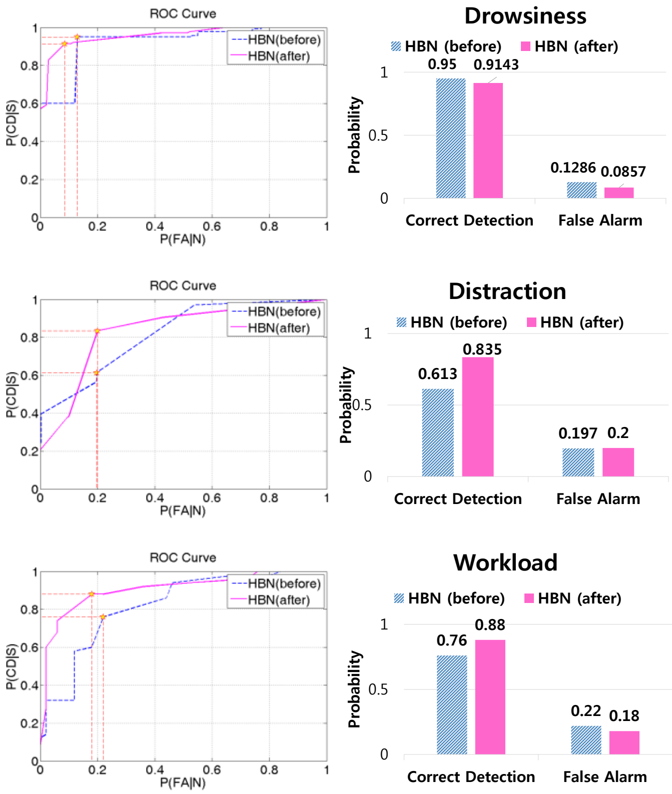

Fig. 4 HBN algorithm performance graphs

same experimental time and distraction/workload occurrence sections were used in the baseline section.

Each driver-state section was divided into data of one to 300 rows. The highest probability in the section was stored in normal and abnormal state variables. Thereafter, whereas a certain threshold k changed from 0 to 1 by increments of 0.01, if the stored abnormal state data were greater than the k value, the number 1 was stored in the result variable. Otherwise, the number 0 was stored. We confirmed a correct detection rate by confirming that the number 1 was stored in the abnormal state result variable. We confirmed a false alarm rate by confirming that the number 0 was stored in the normal state result variable. We next graphed the Receiver Operating Characteristic (ROC) curve using correct detection and false alarms, and then marked the point indicating the best performance. Fig. 4 shows the experimental results. The blue dashed line represents HBN without efficacy analysis, whereas the magenta solid line represents HBN with efficacy analysis. The upper graph in Fig. 4 shows the results of the drowsiness experiment. Although HBN with efficacy analysis has a lower correct detection, the false alarms are even lower compared to those in the other two experiments. The middle graph in Fig. 4 shows the results of the distraction experiment. Although HBN with efficacy analysis has slightly higher false alarms compared to those in the other two experiments, it also shows higher correct detection. The bottom graph in Fig. 4 shows the results of the workload experiment. HBN with efficacy analysis has a higher correct detection and lower false alarm compared to those of the other two experiments.

TABLE II. HBN ALGORITHM PERFORMANCE RESULTS

	HBN (without efficacy)			**HBN (with efficacy)**		
	Drowsiness	***Distraction***	***Workload***	***Drowsiness***	***Distraction***	***Workload***
CD[a]	0.9500	0.6130	0.7600	0.9143	0.8350	0.8800
FA[b]	0.1286	0.1970	0.2200	0.0857	0.2000	0.1800
CT[c]	0.00027	0.00022	0.00021	0.00025	0.00020	0.00020

a. Correct Detection (CD), b. False Alarm (FA) c. Calculation Time (CT)

HBN performance is summarized in Table II. In the drowsiness experiment, HBN without efficacy analysis requires 0.00027 s to estimate the driver-drowsiness state using a single row of data, whereas HBN with efficacy analysis requires 0.00025 s. In the distraction experiment, HBN without efficacy analysis requires 0.00022 s to estimate the driver distraction state using a single row of data, whereas HBN with efficacy analysis requires 0.00020 s. In the workload experiment, HBN without efficacy analysis requires 0.00021 s to estimate the driver-workload state using a single row of data, whereas HBN with efficacy analysis requires 0.00020 s.

IV. CONCLUSION

This study aimed to develop an algorithm to estimate driver states such as drowsiness, distraction, and workload. We obtained actual data by conducting human-in-the-loop experiments. In addition, efficacy analysis was performed. We modeled the HBN algorithm based on the results of efficacy analysis. The algorithm was evaluated using our experimental data. Overall, HBN with efficacy analysis showed high correct detection rates, few false alarms, and fast calculation speed.

However, generalizing the data proved difficult because only a limited number of participants were used. In addition, we were unable to obtain data when errors occurred in the sensor module of the experiment. Because of the limited types of biometric sensors, we expect better results in a future study when a richer data set is employed. In addition, because the video was unable to capture the faces of drivers during the drowsiness experiment, estimating the true abnormal driver state was difficult.

In the future, conducting experiments using participants of different ages and gender is essential. In addition, several sensor modules should be secured to collect various types of data. Moreover, distinguishing between cases of masking and unmasking drowsiness in the sleep-restricted group is necessary.

Acknowledgments

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