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Classification of a Driver's cognitive workload levels using artificial neural network on ECG signals

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ABSTRACT

An artificial neural network (ANN) model was developed in the present study to classify the level of a driver's cognitive workload based on electrocardiography (ECG). ECG signals were measured on 15 male participants while they performed a simulated driving task as a primary task with/without an N-back task as a secondary task. Three time-domain ECG measures (mean inter-beat interval (IBI), standard deviation of IBIs, and root mean squared difference of adjacent IBIs) and three frequencydomain ECG measures (power in low frequency, power in high frequency, and ratio of power in low and high frequencies) were calculated. To compensate for individual differences in heart response during the driving tasks, a three-step data processing procedure was performed to ECG signals of each participant: (1) selection of two most sensitive ECG measures, (2) definition of three (low, medium, and high) cognitive workload levels, and (3) normalization of the selected ECG measures. An ANN model was constructed using a feed-forward network and scaled conjugate gradient as a back-propagation learning rule. The accuracy of the ANN classification model was found satisfactory for learning data (95%) and testing data (82%).

1. Introduction

Cognitive workload and drowsiness during driving are considered major causes of vehicle accidents. The National Safety Council (NSC) reported that cognitive workload causes 21% of all crashes (NSC, 2012). The National Highway Traffic Safety Administration estimated that 100,000 accidents per year in the USA were caused by driver drowsiness (Rau, 2005). Additionally, Aidman et al. (2015), Pack et al. (1995), and Williamson et al. (2011) reported that driver overload and monotony are two significant causative factors in traffic accidents. Therefore, the detection of cognitive workload and drowsiness during driving is important for preventing accidents and hazards on the road (Engström et al., 2005; Verwey and Zaidel, 1999; Wong and Huang, 2009; Collet et al., 2009).

The physiological responses of drivers have been widely used in the detection of cognitive workload and drowsiness in a vehicle. Eoh et al. (2005) and Jagannath and Balasubramanian (2014) observed an increase in alpha and a decrease in beta electroencephalographic (EEG) activity associated with drowsiness. Mayser et al. (2003) found a slight increase in electromyogram (EMG) on the lateral frontalis as cognitive workload was imposed. Genno et al. (1997), Ohsuga et al. (2001), and Yamakoshi et al. (2008) observed a decrease in skin temperature with increased cognitive workload and drowsiness. Lastly, Mehler et al. (2012), Fallahi et al. (2016), and Rodriguez-Ibañez et al. (2012) found a decrease in mean inter-beat interval (IBI) of electrocardiograph (ECG) with increased cognitive workload and an increase in mean IBI with increased drowsiness.

Among the aforementioned physiological responses, ECG is

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considered a reliable measure in estimating a driver's status. ECG signals can be quantified in terms of time and frequency domains. Time domain measures include mean IBI, standard deviation of IBIs (SDNN), and root mean squared difference of adjacent IBIs (RMSSD) (Combatalade, 2010; Juan, 2004). These time domain measures generally decrease when the level of cognitive workload increases (Berntson et al., 1997; Brookhuis and De Waard, 2001; Mehler et al., 2009, 2012; Wood et al., 2002; Fallahi et al., 2016). Frequency domain measures include power in low frequency (LF), power in high frequency (HF), and LF/HF ratio (Calcagnini et al., 1994; Tal and David, 2000; Yang et al., 2010). Generally, the LF and LF/HF ratio increase and the HF decreases as the level of cognitive workload increases (Wood et al., 2002; Fallahi et al., 2016).

On the other hand, there is an individual variation in heart response. Many studies have reported that heart responses to tasks show significant differences between individuals (Hong et al., 2014; Lee et al., 2010; Lal and Craig, 2001). First, an effective ECG measure varies noticeably among individuals. For example, the RMSSD of Driver A in Fig. 1 a changes more by cognitive tasks than other ECG measures, while the mean IBI of Driver B in Fig. 1 b is more distinctly altered than the other measures. Next, heart sensitivity to cognitive tasks of different levels varies individually. For example, a low workload task for Driver A in Fig. 1 a can be differentiated from medium and high workload tasks, while a high workload task for Driver B in Fig. 1 b can be discriminated from low and medium workload tasks. Lastly, the magnitudes of ECG measures also vary among individuals. For example, Driver A in Fig. 1 a shows a smaller mean IBI than Driver B in Fig. 1 b for all cognitive tasks.

Although advanced classification methods have been applied in the detection of drowsiness and cognitive workload, the classification accuracy for cognitive workload needs to be improved. Patel et al. (2011) used an artificial neural network (ANN) to identify the presence of driver drowsiness and reported a classification accuracy of 90%. In addition, Vicente et al. (2011) utilized a linear discriminant analysis to classify a driver into two statuses (awake or drowsy) and presented a specificity of 93% and a sensitivity of 85%. On the other hand, Zhang et al. (2014) applied a regression method to classify the extent of cognitive workload into two levels (normal or elevated workload) and showed an accuracy of 62.5%. Solovey et al. (2014) used five classification methods (decision tree method, logistic regression method, multilayer perceptron method, Naïve Bayes method, and nearest neighbor method) to classify the extent of workload into the two levels and reported an accuracy of 71.5%–74.1%. Although several classification methods have been applied to classify the extent of cognitive workload level, their accuracies are low because they do not consider the individual differences of heart response by cognitive workload in the development of a classification model.

The present study developed an ANN model considering individual differences in classifying the level of a driver's cognitive workload based on ECG data. ECG data were measured while participants performed a simulated driving task as the primary task with/without a working memory task (N-back) as the secondary task. The individual differences in heart response were adjusted at the signal processing stage. The ANN model was trained using a feed-forward network and back-propagation learning rule and then evaluated in terms of sensitivity and specificity.

2. Method and materials

2.1. Participants

Fifteen male participants with at least 3 years of driving experience were recruited in this study. Their average (SD) age was 27.7 (3.0) and the participants were healthy and had no discomfort on the day of experiment. Their participation was compensated.

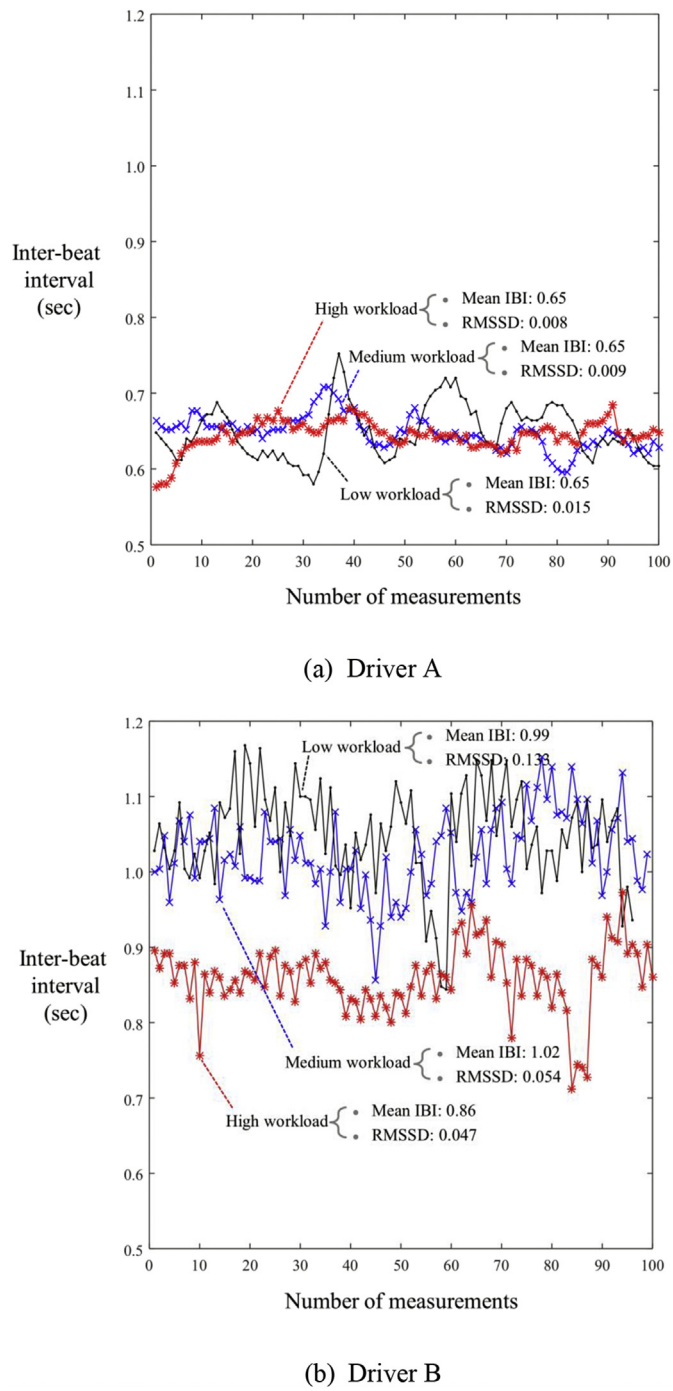


Fig. 1. Illustration of ECG changes based on cognitive workload.

2.2. Equipment

A driving simulator (STISIM Drive™, Systems Technology Inc., USA) was used in this study, as shown in Fig. 2. The driving simulator consisted of a vehicle and a large screen (resolution: 1024 × 768) showing a driving scene. The driving scenario was to drive on a two-lane (width of a lane: 4.57 m) highway at a speed of about 100 km/h.

A MEDAC System/3 ECG system (NeuroDyne Medical Corp., USA) was used to measure ECG signals while the participants drove

Fig. 2. Driving simulator used in this study.

a driving simulator. Three ECG sensors were attached below the left clavicle, right clavicle, and left rib. The sampling rate was set to 250 Hz.

2.3. Experimental design

The participants were instructed to drive (primary task) the driving simulator while performing an N-back task (secondary task). The N-back task was to recall the N step's earlier number when an experiment instructor presented a sequence of arbitrary numbers (Hong et al., 2014; Mehler et al., 2011a; Son et al., 2010). The level of difficulty of the N-back task could be adjusted based on N. Four driving tasks (driving without N-back task, driving with 0-back task, driving with 1-back task, and driving with 2-back task) were performed to simulate multitasking with different levels of difficulty.

The experiment was conducted in four steps. The purpose of the experiment was explained to the participant and informed consent was obtained. Next, ECG sensors were attached to the participant, and practice driving was allowed to be familiarized with the simulator driving and N-back tasks. Then, the main experiment was conducted and ECG data were collected during the four driving tasks lasting 2 min each. Lastly, a debriefing session was conducted.

2.4. Signal processing

Measurements for six ECG measures in time (mean IBI, SDNN, and RMSSD) and frequency (LF, HF, and LF/HF) domains were collected in four steps. First, IBI data were calculated from the raw ECG signals using the R-peak detection algorithm (Billauer, 2012) coded in Matlab (MathWorks, Inc., USA). Second, the IBI data between 10 and 110 s out of those of 120 s were selected in the subsequent analysis (note that data measured during the initial and last 10 s were not included to avoid possible ECG contamination due to the transition effect of a participant's status change from rest to driving or from driving to rest). Third, the three time domain measures were quantified using Equations (1)–(3), respectively. Lastly, three frequency domain measures were obtained by fast Fourier transformation in Matlab. For frequency analysis, this study determined the appropriate time window to be 100 s based on Clifford (2002). The frequency bands for LF (0.04–0.15 Hz) and HF (0.15–0.4 Hz) were defined based on Combatalade (2010).

$$\text{Mean IBI} = \frac{\sum_{i=1}^{n} IBI_i}{n} \tag{1}$$

where: n = number of inter-beat intervals.IBI_i = ith inter-beat interval

$$\text{SDNN} = \sqrt{\frac{\sum_{i=1}^{n} (IBI_i - \overline{IBI})}{n-1}} \tag{2}$$

where: n = number of inter-beat intervals.IBI_i = ith inter-beat interval.$\overline{IBI}$ = average of inter-beat intervals

$$\text{RMSSD} = \sqrt{\frac{\sum_{i=1}^{n-1} (IBI_{i+1} - IBI_i)^2}{n-1}} \tag{3}$$

where: n = number of inter-beat intervals.IBI_i = ith inter-beat interval.

To adjust for individual differences in heart response, the following three-step signal processing procedure was conducted: (1) selection of two sensitive ECG measures, (2) definition of three workload levels, and (3) normalization of the selected ECG measures. In the first step, the two sensitive ECG measures for each participant were selected from the six ECG measures. Since the sensitivities of the ECG measures were different among participants, two ECG measures which best discriminated the driving tasks were selected for each participant. For example, in Fig. 3 a, mean IBI and RMSSD were selected as sensitive measures due to their systematic trend of change with different driving tasks.

In the second step, the three levels of perceived workload were individually defined for each participant by grouping the four driving tasks. Since the level of perceived workload based on the driving tasks varied among participants, the four driving tasks of each participant were grouped into three workload categories (low, medium, and high). For example in Fig. 3b, a participant was less sensitively changed during the driving and driving with 0-back tasks than during other driving tasks. Thus, the participant's perceived workload level was defined as low (driving and driving with 0-back tasks), medium (driving with 1-back task), and high (driving with 2-back task). Detecting the perceived level of cognitive workload is assumed in the present study more important to prevent a vehicle accident. For example, suppose that two drivers (drivers A and B) conduct the same cognitive task (secondary task) while driving (primary task). Driver A with a high mental capability would conduct both the dual tasks without difficulty since the perceived level of cognitive workload is low, while driver B with a low mental capability would not since the perceived level of cognitive workload is high.

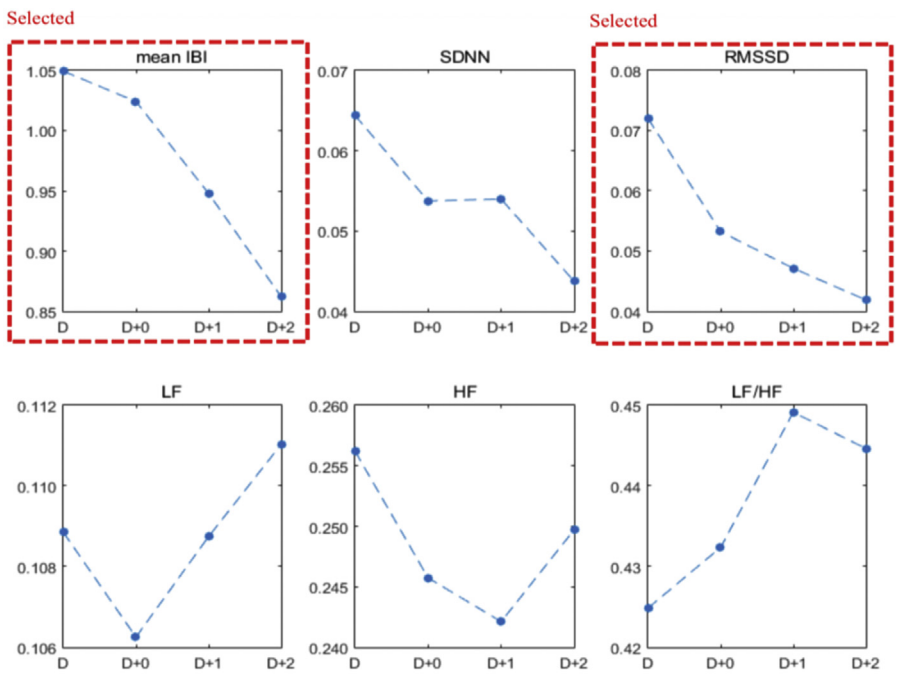
In the last step, the two selected ECG measures were normalized by their median values. The magnitude of the ECG measures varied significantly not only among participants but also among the ECG measures. To obtain values of a common scale, measurements of the selected ECG measures for each participant were normalized using the corresponding participant's median values, which were considered as those of medium workload level. Fig. 3 c illustrates the median normalizing process for a participant using Equation (4). This median normalization can set the medium workload level as a referent. For example, for the normalized ECG value < 1 (smaller than the medium workload level) the perceived workload level is low and for the opposite of the normalized ECG value the perceived workload level is high.

$$\text{N}_i = \frac{x_i}{\tilde{x}} \tag{4}$$

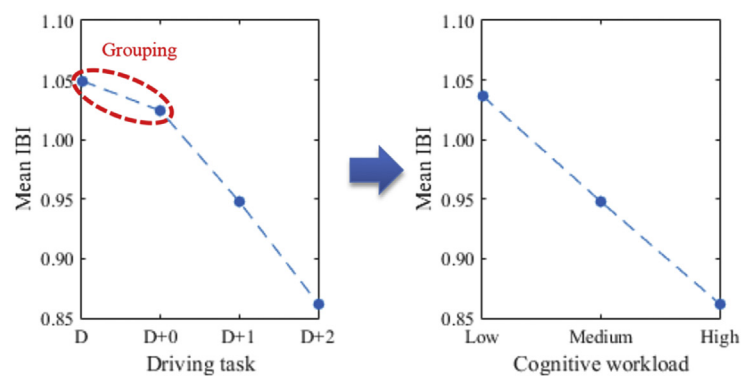
where: N_i = ith normalized data.x_i = ith data.$\tilde{x}$ = median.

2.5. ANN modeling

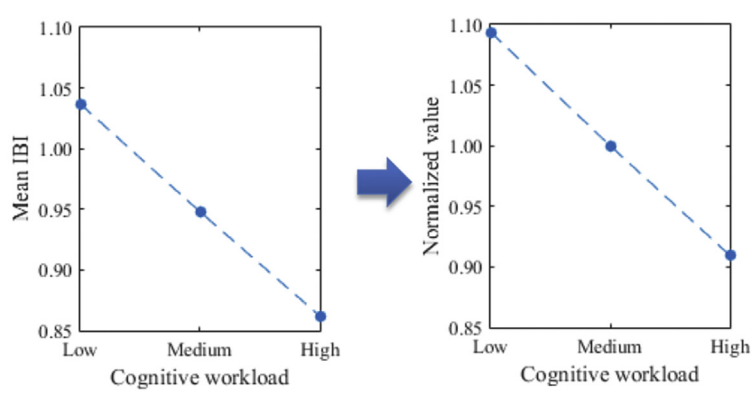
The topology of the ANN model consisted of three layers (input,



(a) Selection of two sensitive ECG measures



(b) Definition of the three workload levels based on driving tasks



(c) Normalization of the ECG measure

Fig. 3. Illustration of correction for individual differences (D: driving, D+0: driving with 0 back task, D+1: driving with 1 back task, D+2: driving with 2 back task).

hidden, and output layers) as shown in Fig. 4. The input layer had two nodes for the two normalized ECG measures. The hidden layer, which processed the normalized ECG measures using the sigmoid activation function, had 15 neurons. The number of neurons in the hidden layer affected the classification accuracy; however, no accepted theory currently exists for predetermining the optimal number of neurons (Acharya et al., 2003). Hence, the optimal number of neurons (15) was determined by varying it from 5 to 30 with an interval of 5 until the network with highest sensitivity and specificity was obtained. The output layer had three nodes, which denoted three levels (low, medium, and high) of cognitive workload.

A standard feed-forward and back-propagation neural network was employed in the present study. A three layer feed-forward network was utilized in the Neural Network Toolbox of Matlab. A hyperbolic tangent sigmoid transfer function was applied as the transfer function of the hidden layer. A linear transfer function was used for the transfer function of the output layer. The scaled conjugate gradient was utilized as a back-propagation network learning function. Lastly, the ECG data of the fifteen participants were randomly divided into learning and testing sets–70% of the ECG data for learning of the ANN model and the remaining for testing.

3. Results

3.1. ECG measures

The time domain measures as shown in Fig. 5 were more sensitive to changes in workload than frequency domain measures, which is consistent with Mehler et al. (2011b). The time domain measures (normalized mean IBI, SDNN, and RMSSD) gradually declined as the workload level increased. For example, the normalized mean IBI was 1.05 (0.80 s) for the low workload, 1.00 (0.77 s) for the medium workload, and 0.94 (0.72 s) for the high workload. Meanwhile, the frequency domain measures (normalized LF, HF, and LF/HF ratio) showed insignificant changes with change in workload. For example, the normalized LF was 0.99 (0.1107 m^2) for the low workload, 1.00 (0.1117 m^2) for the medium workload, and 1.01 (0.1137 m^2) for the high workload.

A one-factor (workload level) within-subject ANOVA test of the six normalized ECG measures revealed that the normalized mean IBI ($F(2, 28) = 17.58$, $p < 0.001$) and normalized RMSSD ($F(2, 28) = 9.84$, $p = 0.001$) were significantly altered by the workload level at $\alpha = 0.05$. Tukey tests classified the workload levels into three groups (Group A: low workload, Group B: medium workload, and Group C: high workload) for the normalized mean IBI and two groups (Group A: low workload, Group B: medium and high workload) for the normalized RMSSD. On the other hand, the normalized SDNN and the three frequency measures showed a systematic trend with the elevation of cognitive workload, but it was not statistically significant (normalized SDNN: $F(2, 28) = 1.64$, $p = 0.212$; normalized LF: $F(2, 28) = 1.84$, $p = 0.178$; normalized HF: $F(2, 28) = 0.91$, $p = 0.414$; normalized LF/HF: $F(2, 28) = 2.42$, $p = 0.108$).

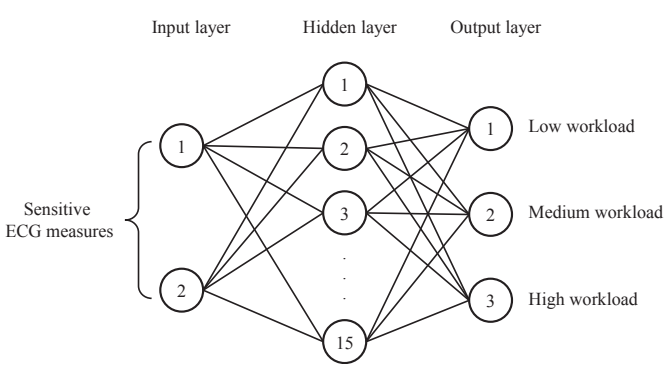


Fig. 4. Three-layer feed-forward neural network structure.

3.2. ANN performance

The classification accuracy of the proposed ANN was satisfactory for both the learning and testing sets. The cross evaluation was repeated 100 times to rigorously validate the performance of the proposed ANN. The average classification accuracies for the learning and testing sets were 95% (SD = 2.77) and 82% (SD = 8.58), respectively. As shown in Fig. 6, sensitivity (true positive rate) and specificity (true negative rate) had no systematic bias in the learning and testing sets.

4. Discussion

An ANN model considering individual differences in heart responses was developed to accurately classify the level of drivers' cognitive workload based on ECG data. Two sensitive ECG measures of each participant were selected to correct the individual difference in the sensitivity of ECG measures. Three levels (low, medium, and high) of cognitive workload were defined for each participant by grouping four driving tasks (driving without N-back task, driving with 0-back task, driving with 1-back task, and driving with 2-back task) to adjust the individual difference in the perceived extent of workload. In addition, the ECG measures were normalized by their

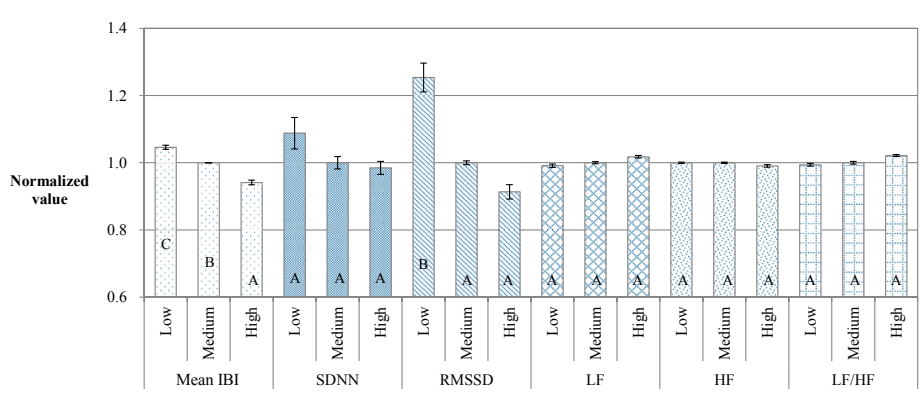


Fig. 5. Normalized ECG measures for different workloads.

Classified workload \ Actual workload	Low	Medium	High	Specification
Low	962	33	6	96%
Medium	86	961	11	91%
High	3	29	1009	97%
Sensitivity	92%	94%	98%	95%

(a) Learning data set

Classified workload \ Actual workload	Low	Medium	High	Specification
Low	366	32	8	90%
Medium	79	413	97	70%
High	4	32	369	91%
Sensitivity	82%	87%	78%	82%

(b) Testing data set

Fig. 6. Confusion matrix.

median values to correct the individual difference in the magnitude of ECG measures. The ANN model developed in this study showed high classification accuracies for both the learning (95%) and testing (82%) data sets.

Mean IBI decreased gradually to come up with an oxygen demand as the workload level increased. The normalized mean IBI in this study was 1.05 for the low workload, 1.00 for the medium workload, and 0.94 for the high workload, which can be explained by the relationship between cognitive workload and oxygen demand. A cognitive load promotes oxygen demand by cells and leads to the production of more cardiac output by increasing heart rate (Brookhuis et al., 1991; Brookhuis and De Waard, 2001; Lenneman et al., 2005; Mehler et al., 2009). Since heart rate is inversely proportional to mean IBI (heart rate = 60 s/mean IBI), increased cognitive load is generally associated with a decrease in mean IBI.

Cognitive workload influenced ECG measures differently from drowsiness and driving fatigue. The mean IBI decreased as cognitive workload increased in this study; while the mean IBI increased as drowsiness (Lal and Craig, 2001; Rodriguez-Ibañez et al., 2012) or driving fatigue (Lal and Craig, 2002; Li et al., 2004; Zhao et al., 2010; Milosevic, 1997) increased. In addition, the LF/HF ratio calculated in this study increased when the difficulty of the workload increased; on the other hand, the LF/HF ratio significantly decreased with drowsiness (Elsenbruch et al., 1999; Tasaki et al., 2010; Miyaji, 2014) or driving fatigue (Calcagnini et al., 1994; Patel et al., 2011; Yang et al., 2010). Thus, it is implied that cognitive workload modulates the sympathetic and parasympathetic nervous systems in an opposite manner from drowsiness and driving fatigue.

The proposed ECG-based cognitive workload assessment methodology can be applied to the development of a system that can identify the periods of driver's elevated cognitive workload. The ANN model developed in the present study showed good classification accuracies; thus, it might be applied for developing an intelligent vehicle in order to inform or support the driver in a variety of ways. For instance, an intelligent vehicle provides biofeedback to the driver about becoming over aroused; then, the driver will modify or control his behavior to return to the optimal level of arousal. The biofeedback information needs to be provided to assist the driver without any distraction (Coughlin et al., 2011). Alternatively, output from a biofeedback system can be transferred into a workload management system that reduces sources of distraction through actions, such as blocking incoming phone calls when the driver is under periods of high workload (Andreone et al., 2005; Green, 2004).

However, the proposed methodology has a weakness because learning over a certain period of time is required to select two distinctive ECG measures for each driver. Although the step of selecting distinctive ECG measures can improve the accuracy of a classification model by personalizing to an individual driver, the learning step needs some time from a driver before activating a biofeedback system in the driving context.

Three future researches are needed to enhance the applicability of the proposed ANN model in the development of an intelligent vehicle. First, an in-depth evaluation for various age and gender groups is required to comprehensively understand the relationship between cognitive workload and ECG measures. Second, further research is needed to investigate the effect of different workload tasks on distinctive ECG measures of an individual driver. Two distinctive measures for each individual were selected while doing the N-back task and the selected ECG measures might be biased to the cognitive task employed in this study. Therefore, a study is needed to examine if the distinctive ECG measures of an individual driver are identical or changed by different cognitive tasks. Lastly, a field study is needed to validate the results of the present study because the experiment in the present study was conducted in a driving simulator in which driving conditions and environment were controlled.

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