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Detection and Predictive Analysis of Drowsiness Using Non-contact Doppler Sensor

Chung Kyo In, Byung Chan Min*

Abstract: The demand for continuous monitoring of vital signs is steadily increasing. Drowsiness occurs when individuals are tired or engaged in repetitive tasks, and driving or working in this state can lead to serious accidents. Various methods for detecting heartbeats based on Doppler sensors have been proposed due to their non-contact nature. Previous research involved developing Doppler radar sensors and verifying their reliability, with over 95 % accuracy compared to traditional ECG devices for heart rate measurement. This study proposes a method utilizing existing Doppler radar sensors to detect and predict drowsiness. To verify the test subjects' drowsy states, their faces were recorded with a camera, and the moments when their eyes were closed were validated as instances of drowsiness. Analytical methods were employed, including cross-method analysis, logistic regression analysis, and panel logistic regression analysis. The analysis revealed a p-value for drowsiness detection lower than 0.001, indicating statistical significance. Moreover, the significance of drowsiness states and stages was confirmed with an accuracy of over 95 %. Particularly, panel logistic regression analysis suggested its suitability as an indicator for predicting drowsiness states. In terms of predicting drowsiness stages and actual drowsiness states, it was observed that a time error of approximately 20-30 seconds exists. The study aimed to detect drowsiness and predict drowsiness based on data acquired through a non-contact Doppler radar sensor.

Keywords: cross analysis; Doppler radar sensor; drowsiness; logistics regression; RRI

1 INTRODUCTION

Drowsiness is akin to falling asleep and is triggered when the body is physically or mentally tired in response to the need for rest. The primary factor that causes drowsiness is the secretion of melatonin, a sleep hormone. Drowsiness can also be induced when there is a high concentration of carbon dioxide in the air or when the environment is warm. Drowsiness is particularly likely to occur during monotonous, repetitive, and demanding tasks, a notable example being driving. Drowsiness can unconsciously creep when handling a steering wheel in a fatigued state, especially during extended high-speed highway driving. On highways, where driving at high speeds is common, driving accidents related to drowsiness can lead to a significant loss of life. Therefore, many studies have focused on detecting drowsiness in advance while driving or working to prevent drowsy driving and industrial accidents.

The method of determining drowsiness based on bio-signals uses electrocardiograms and brain waves, and many studies have been conducted relatively recently. Drowsiness detection technology based on biological signals is accurate, but it has the disadvantage of being uncomfortable for the driver and making conscious judgments because electrodes are attached directly to the driver's body. Therefore, in this study, we develop a program that detects drowsiness based on bio-signals in a non-contact state and analyze the accuracy of drowsiness prediction through experiments.

In a previous study, a Doppler radar sensor was developed and heart rate was measured and analyzed in a non-contact manner. As a result of the measurement, more than 95% accurate reliability was secured compared to existing ECG equipment.

In this study, we present drowsiness and prediction accuracy through a Doppler radar sensor system that remotely detects the breathing and heart rate signals of a stationary target located at a distance of 1 m or less. The proposed radar sensor system is implemented with a 24 GHz band high-sensitivity sensor module to transmit and receive unique operating frequency signals and a signal processing technique to detect biological signals in real time and monitor changes. As a result of measuring nine subjects using a Doppler radar sensor, it was shown that the proposed radar sensor can monitor breathing rate and heart rate per minute with a detection accuracy of over 95%.

In Chapter 2, a program that can detect drowsiness is developed using data acquired from a Doppler radar sensor, and three analysis methods, including cross-tabulation, logistic regression, and panel logistic regression, are used to predict drowsiness. A prediction of drowsiness was presented through this study. Chapter 3 presents the time difference results for whether or not drowsiness is detected and prediction based on the detection results of bio-signals measured from the subject. Chapter 4 discusses various application fields and mentions future research development directions.

In future study, we plan to conduct research that can not only detect drowsiness but also test bio-signals in a non-contact manner by replacing the existing electrocardiogram measurement method in the medical field.

2 METHODS

2.1 RRI Algorithm Analysis

This study aimed to improve peak and drowsiness detection accuracy through Doppler-sensor-based *RRI* (R-R interval) analysis. Fig. 1 presents a flowchart of the proposed *RRI*, which consists of three stages. The first stage involves preprocessing, the second involves spectrum extraction, and the final involves estimating the *RRI* (R-R intervals).

In the pre-processing stage, a Bandpass Filter (BPF) was used to remove frequency components other than the heartbeat, such as respiration and minor movements. Subsequently, short-term Fourier transform (STFT) was applied to calculate the spectrum. To extract the spectrum related to heartbeats, the time window used in STFT should be shorter than that of *RRI* and encompass only one heartbeat.

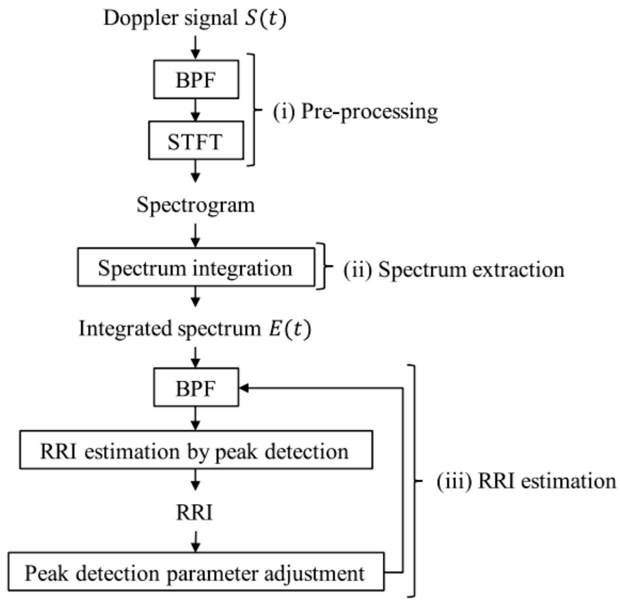

Figure 1 The Flowchart of the RRI method

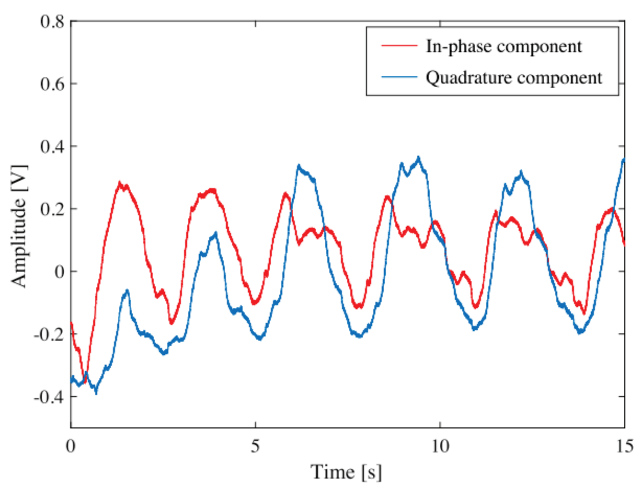

Figure 2 An Examples of in-phase and quadrature components

Fig. 2 provides examples of the interface and quadrature components. Fig. 3 shows eight peaks observed within the window, some related to heartbeats, whereas others are due to noise. Therefore, only the peaks associated with the heartbeats should be selected. Among the 1, 2, 3, ..., 8 peaks, three peaks, p_1, p_2, p_3 ($p_1 < p_2 < p_3$), are selected so that the differences between the previously predicted *RRI* (RRI_{prev}) and the two pairs of *RRI*s are minimized. This was because the adjacent *RRI*s did not vary significantly. Assuming that RRI_{prev} is accurately estimated in Fig. 3, peak 1 is selected as p_1. Subsequently, pairs $RRI_{1,k}$ ($2 < k < 8$) and $RRI_{k,m}$ ($k < m < 8$) were generated. Peaks 1, 3, and 5 are chosen as the final selection for p_1, p_2, and p_3, satisfying the condition that the difference between RRI_{prev}, $RRI_{1,k}$, and $RRI_{k,m}$ is the smallest. Because *RRI*s do not vary significantly between adjacent *RRI*s, a time window is set using the previously estimated *RRI* (RRI_{prev}). If we set the maximum difference between the current *RRI* and the previous *RRI* as 1, when *RRI* increases consecutively twice, the current *RRI* (RRI_{curr}) will equal $RRI_{prev} + 1$, and the next *RRI* will be $RRI_{curr} + 1$, which is $RRI_{prev} + 21$. Therefore, the length of time window W was set according to Eq. (8). This ensured that the window included exactly 3 heartbeats.

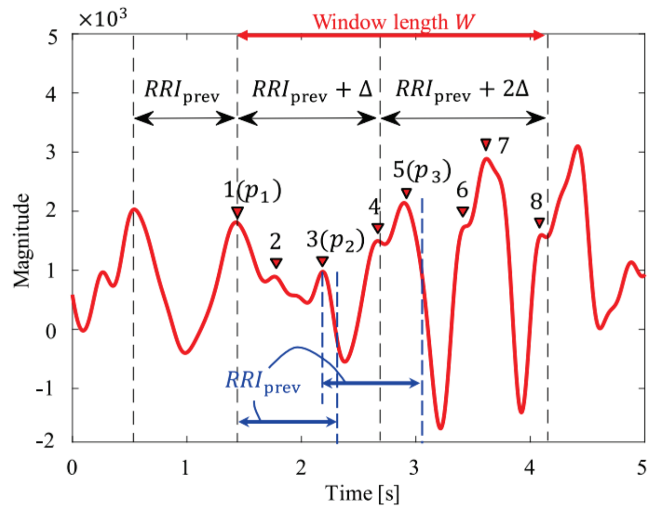

Figure 3 A Concept of the Proposed Peak Detection Algorithm

2.2 Development of Drowsiness Detection Program

This program extracts three main types of data: heart rate, *HRV* (Heart Rate Variability), and drowsiness levels. After specifying the duration of the experiment, data were automatically saved when the set time expired.

The data were stored under folder names, as shown in Tab. 1.

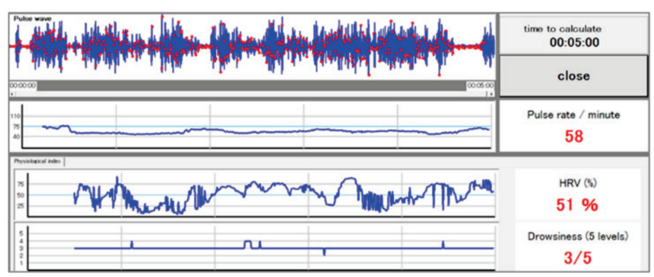

Figure 4 Drowsiness detection program

Table 1 Data file savings

File Name	Example	Description
*****.dat	No_191015155525.dat	Copy of raw data files used for offline analysis. The filename remains the same as the imported file.
No_Processing time.csv ※Saved for offline processing	No_191104131358.csv	Heart Rate, HRV
No_Processing time RR.csv ※Saved for offline processing	No_191104131358_RR.csv	Time (HH:mm: ss.msec) of waveform correction detection and the numerical value of RR interval (msec) for the correction interval concerning input data.

2.2.1 Driving Fatigue and Physiological Index

The drowsiness stage was derived by analyzing the standard deviation of the RR interval, and the RR interval data from the pulse wave peak were resampled and corrected, as shown in Fig. 5.

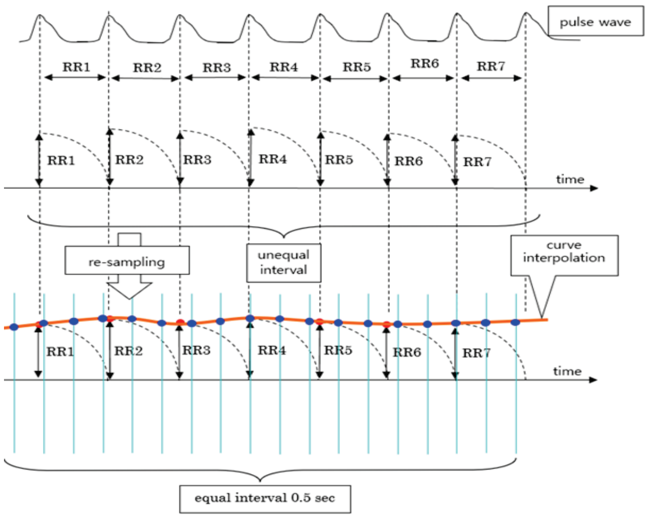

Figure 5 Standard deviation analysis of RR interval

Calculate the power spectrum density of the equally spaced RR interval data, calculating the power between 0.04 and 0.15 Hz as LF and the power between 0.15 and 0.4 Hz as HF.

2.3 Subjects

Nine healthy male and female university students with no cardiovascular or respiratory disorders participated in the experiment. The experiment involved distinguishing between the wakefulness and drowsiness states of each participant. Wakefulness state measurements were taken in the morning, while drowsiness state measurements were conducted after participants stayed awake as late as possible the previous day, and drowsiness was induced by eating a heavy lunch the following day.

2.4 Test Procedure

The participants were instructed to achieve a stable state for 10 min and keep their eyes closed if drowsiness was induced. A camera was placed in front of the participants, and drowsiness was measured using a Doppler sensor. The camera recorded the time displayed on the program, and the moment the participants' eyes closed was used to indicate drowsiness. Drowsiness is detected using this criterion (Tab. 2).

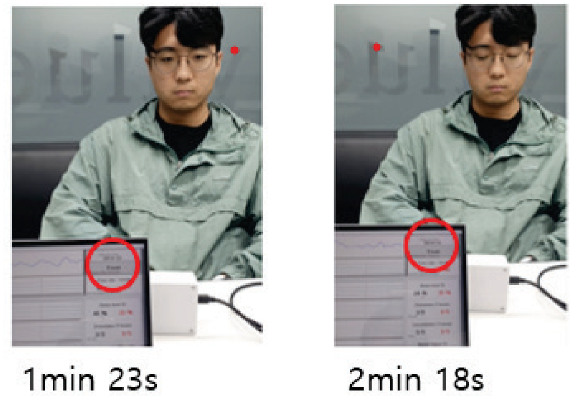

Table 2 Drowsiness detection experiment

Time	Pulse rate	drowsiness	drowsiness (auxiliary number)	Note
0:00:00	78.2354	0	0	
	78.0948	0	0	
	76.0561	0	0	
	76.3104	0	0	
	77.9916	0	0	
	80.3826	3	256.4692	
	78.066	3	244.5294	
	73.8956	3	249.8995	
0:02:18	70.819	3	257.4451	Subject's actual time of drowsiness
	70.819	3	257.4451	
	69.4248	3	254.3162	
	71.1686	3	255.33	
	72.909	3	247.123	
0:02:54	49.7231	4	145.2678	Doppler sensor drowsiness detection time
	49.7231	4	145.2678	
	49.4186	4	144.8847	
	46.4945	4	124.442	
	49.5174	4	148.3674	
	49.6452	4	146.8294	
	49.9585	4	138.2954	
	46.5547	4	117.7181	
	46.5547	4	117.7181	
	46.4956	4	120.5528	
	46.6686	4	115.6547	
	46.4956	4	120.5528	
	45.1074	4	83.6849	
	45.1074	4	83.6849	

2.5 Experimental Analysis Method

This study aims to determine the accuracy of drowsiness detection and prediction using a Doppler sensor. For this experiment, the independent variable data (heart rate) were collected from nine participants, and the program screen was recorded to document the onset of drowsiness. Specifically, by recording the process leading to drowsiness in the wakefulness state and changes in the independent variable, data were collected from nine participants, creating a panel dataset with time information. The independent variable was a continuous variable ranging from 0 to 5, and the dependent variable was coded as 0 for the wakeful state and 1 for the drowsy state. In this study, the following analyses were conducted to verify the hypothesis that as the drowsiness stage increased, the participants were more likely to be in a drowsy state.

First, to examine the descriptive statistics for drowsiness stages and states without differentiation by time, cross-analysis and decision trees were used to assess prediction accuracy.

Second, logistic regression analysis was conducted to determine whether the likelihood of being in a drowsy state increased as the drowsiness stage increased without differentiation over time.

Third, panel logistic regression analysis was conducted using the panel dataset to determine whether the likelihood of being in a drowsy state increased as the drowsiness stage increased. Additionally, a lag of 10-second intervals was used to estimate the degree of temporal error in predicting the drowsy state based on the drowsiness stage.

2.5.1 Cross-analysis

A cross-analysis (chi-square test) was used to compare the frequencies of the two different qualitative variables to identify and analyze their associations. The equation for the cross-analysis is as follows:

$$\chi^2(chi-sqaure) = \sum\left(\frac{(O-E)^2}{E}\right). \tag{1}$$

O is the observed frequency (the actual observed frequency in the contingency table after cross-analysis), and E is the expected frequency (when there is no statistical association between the two variables). The value of χ^2 increases when the observed frequency is greater than the expected frequency, and conversely, the p-value decreases, indicating a statistically significant difference. Based on this, the following hypotheses were formulated: The hypothesis for this study, which examines the relationship between drowsiness and drowsiness states, is as follows: Null Hypothesis (H0): There is no association between the response categories of drowsiness and drowsiness states. Alternative Hypothesis (H1): There is an association between the response categories of drowsiness and drowsiness state. In accordance with this hypothesis, the cross-analysis result for the drowsiness stage and drowsiness state yielded a χ^2 value of 1936.208, and the p-value was less than 0.001. The statistical significance level was set at $p < 0.05$. Therefore, the null hypothesis, which suggests no significant association between the two variables, was rejected, and the alternative hypothesis, indicating an association between the response categories of the two variables, was supported. Based on these results, it can be concluded that there is a statistically significant difference in the ratio of drowsiness and wakefulness states based on the drowsiness stage. Specifically, when examining these values, it was observed that lower drowsiness stage values corresponded to a higher proportion of wakefulness states, and as the drowsiness stage values increased, the proportion of drowsiness states also increased.

Table 3 Analysis of wakefulness and drowsiness states using cross-analysis

Drowsiness Status					
Drowsiness Stage	Drowsiness wakefulness State	Drowsiness State	Total	χ^2	p
0	308 (100%)	0 (0%)	308	1936.208***	<0.001
2	20 (100%)	153 (88.439%)	173		
3	996 (100%)	6815 (87.249%)	7811		
4	0 (100%)	682 (100%)	682		
5	0 (100%)	35 (100%)	35		
total	1324	7685	9009		
* $p < 0.05$					

A Decision Tree algorithm was used to analyze the data and determine combinations of rules that could predict patterns. This was used to assess the prediction accuracy of the drowsiness stage and drowsiness state. When predicting the actual drowsiness state based on the drowsiness stages in Fig. 7 and Fig. 8, it was observed that there were samples with high prediction accuracy (=.92) and samples with relatively low accuracy (=.68). To quantify this further, a logistic regression analysis was performed.

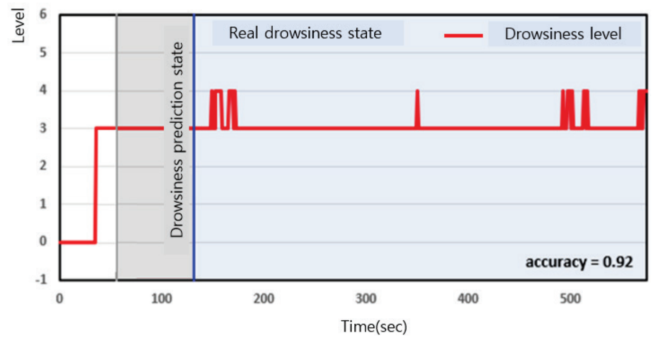

Figure 6 Drowsiness and drowsiness state (Accuracy 92%)

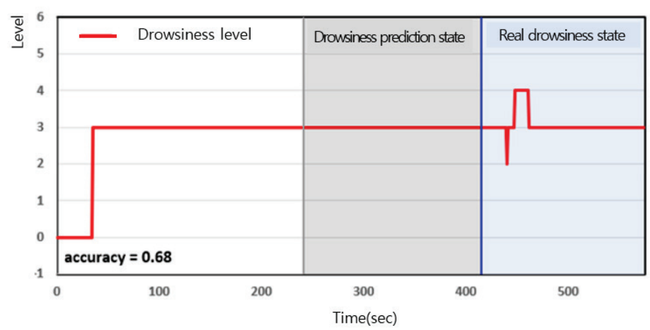

Figure 7 Drowsiness and drowsiness states (Accuracy: 68 %)

2.5.2 Logistic Regression Analysis

Due to its focus on the differences in response frequencies within each cell, cross-analysis has the limitation of being unable to precisely determine how the likelihood of being in a drowsy state increases as the drowsiness stage increases. To address this, logistic regression analysis was employed to provide insight into the probability of being in a drowsy state as the independent variable, the drowsiness stage, increased. The Eq. (2) for the logistic regression analysis is as follows:

$$\text{logit} = \ln\left(\frac{p(x)}{1-p(x)}\right) = \beta_0 + \beta_1 x_1 + \varepsilon. \tag{2}$$

Using a logistic regression model, the analysis aimed to determine the extent to which the likelihood of being in a drowsy state increased as the value of the drowsiness stage increased. The logistic regression analysis results, which predicted drowsiness state as the drowsiness stage increased, showed that the drowsiness stage had a significance level of less than 0.001, making it statistically significant. The Odds Ratio (OR), which indicated how many times the likelihood of being in a drowsy state increased as the drowsiness stage increased by one level, was calculated as 5.554. Thus, it can be concluded that as the drowsiness stage increases by one level, the likelihood of being in a drowsy state increases significantly by approximately 5.554 times.

Table 4 Logistic Regression Analysis Results

	OR	Significance Level	95% C.I. of EXP(B)	
			Lower	Upper
Drowsiness Stage	5.554***	<0.001	4.765	6.474
Constant	0.0427***	<0.001		
* $p < 0.05$				

2.5.3 Panel Logistic Regression Analysis

While logistic regression analysis can reveal the impact of the drowsiness stage on the drowsiness state, this study further examined the relationship between the drowsiness stage and the drowsiness state by conducting a panel logistic regression analysis using panel data from all nine participants. Moreover, considering the potential time lag in the effect of the drowsiness stage on predicting the drowsiness state, logistic regression analysis was performed using 10-second lags for the drowsiness stage. The analysis showed that as the drowsiness stage increased, the likelihood of drowsiness increased significantly by approximately 2.082 times (*OR* = 2.082, $p < 0.001$). Furthermore, the results for each 10-second lag are as follows:

With a 10-second lag, as the drowsiness stage increased, the likelihood of being in a drowsy state significantly increased by approximately 2.098 times (*OR* = 2.098, $p < 0.001$).

With a 20-second lag, as the drowsiness stage increased, the likelihood of being in a drowsy state significantly increased by approximately 2.105 times (*OR* = 2.105, $p < 0.001$).

With a 30-second lag, as the drowsiness stage increased, the likelihood of being in a drowsy state significantly increased by approximately 2.015 times (*OR* = 2.015, $p < 0.001$).

With a 40-second lag, as the drowsiness stage increased, the likelihood of being in a drowsy state significantly increased by approximately 1.857 times (*OR* = 1.857, $p < 0.001$).

With a 50-second lag, as the drowsiness stage increased, the likelihood of drowsiness significantly increased by approximately 1.874 times (*OR* = 1.874, $p < 0.001$).

With a 60-second lag, as the drowsiness stage increased, the likelihood of being in a drowsy state significantly increased by approximately 1.792 times (*OR* = 1.792, $p < 0.001$).

With a 70-second lag, as the drowsiness stage increased, the likelihood of being in a drowsy state significantly increased by approximately 1.749 times (*OR* = 1.749, $p < 0.001$).

With an 80-second lag, as the drowsiness stage increased, the likelihood of being in a drowsy state significantly increased by approximately 1.764 times (*OR* = 1.764, $p < 0.001$).

With a 90-second lag, as the drowsiness stage increased, the likelihood of being in a drowsy state significantly increased by approximately 1.862 times (*OR* = 1.862, $p < 0.001$).

By analyzing these results, it was observed that the *OR* values decreased to 2 or below after 30 s. Among the lag values, the *OR* values were highest between 20 s and 30 s, indicating a strong and statistically significant relationship between drowsiness and drowsiness states. A time lag of approximately 20-30 s (*OR* = 2.105, $p < 0.001$) appeared to offer the highest prediction accuracy for the relationship between drowsiness and drowsiness states.

	Drowsiness state									
Drowsiness level	2.082*** -23.04									
lag1_(10 sec)		2.098*** -23.65								
lag2_(20 sec)			2.105*** -23.82							
lag3_(30 sec)				2.015*** -21.96						
lag4_(40 sec)					1.857*** -19.64					
lag5_(50 sec)						1.874*** -18.14				
lag6_(60 sec)							1.792*** -16.83			
lag7_(70 sec)								1.749*** -16.03		
Lag8_(80 sec)									1.764*** -15.54	
Lag9_(90 sec)										1.862*** -15.56
_cons	-4.281***	- 4.043***	- 3.643***	-2.867**	-1.715	-1.054	1.266	4.654***	3.216***	7.128***
lnsig2u	1.207*	1.384**	1.635***	1.921***	2.467***	2.719***	3.479***	4.138***	3.888***	4.598***
t	-2.54	-2.9	-3.42	-4	-4.58	-5.1	-5.45	-40.84	-5.96	-82.35
N	9009	8919	8829	8739	8649	8559	8469	8379	8289	8199

* p<0.05 ** p<0.01 *** p<0.001

Figure 8 Panel logistic regression analysis results

3 CONCLUSIONS

The results of this study were an experiment on non-contact continuous monitoring using Doppler radar technology, and it was confirmed that drowsiness detection and drowsiness prediction were possible by developing a drowsiness detection program.

Summarizing the analysis results, a significant relationship between the drowsiness stage and drowsiness was confirmed through cross-and decision tree analyses. Among stages 1–5, drowsiness began at stage 3 or higher and was confirmed in more than 95 % of stages 4 and 5.

Next, the intensity of the drowsiness state was confirmed as the drowsiness level increased through a logistic regression analysis. The sample in this study was 9 people, and by panelizing each sample and time, it was confirmed that the drowsiness stage increased the likelih drowsiness.

Finally, to verify the degree of temporal error when the drowsiness stage predicted the drowsiness state, a lag of 10 s was used for each drowsiness stage to identify the section that best explained the drowsiness state.

The drowsiness prediction results of this study can be of great significance in providing a basis for accurately determining the timing of drowsiness. Previous research has simply been to detect drowsiness, but the core of this study is to accurately predict the timing of drowsiness. Therefore, based on the results of this study, it can be hoped that traffic accidents can be prevented in advance by applying an accurate prediction method for drowsiness to drowsy driving.

4 DISCUSSION

In previous research, a Doppler sensor was developed to ensure the reliability of heart rate measurements. This study was conducted on drowsiness detection using a Doppler sensor. As part of our research, we developed a dedicated program for drowsiness detection and analyzed its reliability of drowsiness detection using three analysis methods.

During the study, a slight lag was found between the participants' actual onset of drowsiness and the moment when the Doppler sensor detected it. Because accidents caused by drowsy driving generally occur after a driver becomes aware of drowsiness, it is important to predict drowsiness before it is consciously recognized.

Although it will take some time for this technology to be applied in real life, it could overcome the shortcomings of traditional monitoring methods using body contact in many applications.

In future research, we believe it will be necessary to further increase the number of experimenters and analyze more accurate data using artificial intelligence-based data correction.

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Authors' contacts:

Chung Kyo In
Department of Industrial Management Engineering, Hanbat National University,
125, Dongseo-daero, Yuseong-gu, Daejeon, Republic of Korea
inboss@gmail.com

Byung Chan Min
(Corresponding author)
Department of Industrial Management Engineering, Hanbat National University,
125, Dongseo-daero, Yuseong-gu, Daejeon, Republic of Korea
bcmin@hanbat.ac.kr