1. INTRODUCTION

Many attempts have been made to develop technologies for detecting car driver’s drowsiness by biometric sensors [1-3]. Drowsiness during driving is characterized by the state of fighting with sleepiness, which causes physiological conditions different from those observed during natural processes followed by sleep for resting. We have previously reported that drowsiness during driving is accompanied by typical heart rate pattern named Dip & Waves (Figure 1) [4]. In contrast to conventional heart rate variability (HRV) indices, which reflect averaged features over minutes, Dip & Waves is a feature of wave form appearing transiently with individual drowsiness episodes. While the conventional HRV can be analyzed by selecting stable data segments, the detection of Dip & Wave requires continuous analysis of beat-to-beat intervals. However, it is hard to continuously record stable heartbeat interval signals during driving in a way that does not burden the drivers [5].

In a previous study of polysomnographic analysis during the maintenance of wakefulness test in patients with sleep apnea [6], we observed that about one third of Dip & Waves of R-R interval is accompanied by the changes in respiratory pattern consisting of deep inhalation followed by deep expiration with increased respiration period, which are consistent with those known to accompany yawning [7] (Figure 2). These observations suggest the possibility that respiratory signal may be used for detecting drowsiness during driving. Recently, smart-shirt wearable devices that allow continuous monitoring of stable data segments, the detection of Dip & Wave requires continuous analysis of beat-to-beat intervals. However, it is hard to continuously record stable heartbeat interval signals during driving in a way that does not burden the drivers [5].

In a previous study of polysomnographic analysis during the maintenance of wakefulness test in patients with sleep apnea [6], we observed that about one third of Dip & Waves of R-R interval is accompanied by the changes in respiratory pattern consisting of deep inhalation followed by deep expiration with increased respiration period, which are consistent with those known to accompany yawning [7] (Figure 2). These observations suggest the possibility that respiratory signal may be used for detecting drowsiness during driving. Recently, smart-shirt wearable devices that allow continuous monitoring of

Figure 1: A 10-min heartbeat interval time series a male subject who complained of strong drowsiness while operating a driving simulator. The X-axis and Y-axis represent clock time and heartbeat interval (ms), respectively. Horizontal arrows indicate heartbeat interval fluctuations in the Dip & Waves pattern.
respiration have become available. In the present study, we examined whether the driver drowsiness can be detected from the respiration signal obtained by this method.

2. METHODS

2.1 Protocol

We studied 9 healthy subjects (seven males and two females; age, 45 ± 9 y). Six of them drove a track and three drove a personal car, during which biosignals were monitored with wearable sensors. The protocol of this study has been approved by the Ethic Review Committee of Nagoya City University Graduate School of Medical Sciences and Nagoya City University Hospital (No. 60-18-0211).

2.2 Measurements

Respiration, ECG, and acceleration signals during driving were recorded with a smart shirt biometric sensor system (Hexoskin, Carre Technologies Inc., Montreal, Quebec, Canada, Figure 3). This system was composed of a smart shirt and a data logger in a shirt pocket. The shirt was made of smart garment sensors by which respiratory movements were measured. On the back of the shirt, electrocardiogram (ECG) electrodes were placed and triaxial acceleration sensor was attached to the shirt. Collected bio-signals were stored on the logger, uploaded to the cloud, and analyzed by custom software (VitalRecorder2, Kissei Comtec, Matsumoto, Nagano, Japan). ECG, respiration, and triaxial acceleration signals were sampled at 256, 128, and 64 Hz, respectively. Additionally, simultaneous recording of ECG and acceleration signals on the Holter ECG recorder (Cardy pico 303+, Suzuken Co., Ltd., Nagoya, Japan) was performed as a backup to ensure stable ECG monitoring. The Holter recorder collected ECG signals at 125 Hz and 10 bit (0.02 mV/digit) and triaxial acceleration signals at 32 Hz.

2.3 Data analysis

The respiration signal obtained by the shirt sensor was analyzed by complex demodulation [8, 9], by which respiratory frequency within 0.05–0.45 Hz band was demodulated continuously as functions of time. From the obtained respiratory frequency, respiratory rate variability (RRV) was assessed as the % deviation from the 5-point (5 min) moving average of respiratory frequency.

Holter ECG was analyzed by an ECG scanner (Cardy Analyzer 05, Suzuken Co., Ltd., Nagoya, Japan) and beat-to-beat R-R interval time series were obtained at a time resolution of 8 ms.

Drowsiness during driving was estimated from the heart rate pattern characteristic to Dip & Waves. According to the definition shown in Figure 4, Dip & Waves was detected from R-R interval time series obtained from the Holter ECG.

R-R interval time series were also analyzed for the conventional HRV indices. Using complex demodulation, the amplitudes of very-low-frequency (VLF; 0.0033–0.04 Hz), low-frequency (LF; 0.04–0.15 Hz), and high-frequency (HF; 0.15–0.4 Hz) component were demodulated continuously and averaged over every minute.
All signals, including breathing rate, heart rate, and their variability, are averaged every minute with a common segmentation, and during driving, one-minute segments in which at least one Dip & Waves was detected were annotated as a driving period with Dip & Waves.

2.4 Statistical analysis

The SAS program package (SAS Institute, Cary, NC, USA) was used for statistical analysis. RRV and HRV metrics were compared among three states, non-driving, driving without Dip & Waves, and driving with Dip & Waves, by the analysis of variance (ANOVA) using the Mixed model procedure with subject as the random effect. The changes in respiratory metrics preceding a Dip & Waves were evaluated by repeated measures ANOVA with the Mixed procedure with minute to Dip & Waves as the fixed effect and subject as the random effect. Post-hoc comparisons were performed against a control value that was defined as a 5-min average between 10 and 15 min before the Dip & Waves. Statistical significance was considered with a type 1 error level of 0.05.

3. RESULTS

A total of 8,880 min of signal were obtained (6,521, 1979, and 380 min during non-driving period, driving period without Dip & Waves, and driving period with Dip & Waves, respectively).

During the driving with and without concomitant Dip & Waves, heart rate was higher and SDRR and VLF, LF, and HF amplitudes were lower than during the non-driving period, but respiratory rate did not differ significantly between the driving and non-driving periods (Table 1). Although RRV during the driving period with Dip & Waves was higher than that during the non-driving period, RRV during the driving period without Dip & Waves did not differ significantly from that during the non-driving period. There was no significant difference in heart rate or respiratory rate between the driving periods with and without Dip & Waves, but SDRR, VLF, LF, and HF amplitude, and RRV were greater during the driving period with Dip & Waves than during the driving period without Dip & Waves.

The analyses of temporal trends of metrics prior to Dip & Waves are shown in Table 2 and Figure 5. During 10 min prior to Dip & Waves, no significant changes or time-dependent trend in SDNN, or VLF, LF, or HF amplitude, although heart rate showed an indefinite yet significant changes (Table 2). There was no significant

| Table 1: Heart rate, respiratory, and their variability metrics during non-driving, driving without Dip & Waves, and driving with Dip & Waves |
|-------------------------------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Non-driving                                     | Driving DW (-)  | DW (+)          | ND vs DW(-)     | ND vs DW(+)     | DW(-) vs DW(+)  |
| HR, bpm                                         | 80 ± 16         | 86 ± 17         | <.0001          | <.0001          | 1.0             |
| RR, cpm                                         | 16 ± 5          | 16 ± 5          | 17 ± 6          | 1.0             | 0.2             |
| SDRR, ms                                        | 33 ± 23         | 24 ± 11         | 27 ± 11         | <.0001          | 0.02            |
| VLF, ms                                         | 31 ± 25         | 21 ± 14         | 24 ± 14         | <.0001          | 0.07            |
| LF, ms                                          | 18 ± 19         | 16 ± 10         | 22 ± 9          | <.0001          | 0.001           |
| HF, ms                                          | 23 ± 14         | 18 ± 6          | 21 ± 7          | <.0001          | <.0001           |
| RRV, %                                          | 14 ± 12         | 15 ± 10         | 18 ± 12         | 0.3             | <.0001           |

Values represent mean ± SD.
BF = breathing frequency, DW = Dip & Waves, HF = high-frequency, HR = heart rate, LF = low-frequency, ND = non-driving, RR = respiratory rate, RRV = respiratory rate variability, SDNN = standard deviation of R-R interval, VLF = very-low-frequency.
changes or trend in respiratory rate as well, but RRV increased progressively from 4 min before Dip & Waves (Figure 5). RRV peaked at Dip & Waves and then decreased immediately thereafter.

The x axes represent time from the onset of a Dip & Waves (time 0 is the point where Dip & Waves occurred). 

P values are the overall significance of the effect of time. 

*P < 0.05 against control values (5-min average between 10 and 15 min before the Dip & Waves).

4. DISCUSSIONS

Using data corrected with a smart-shirt wearable biometric sensor in healthy subjects, we analyzed the changes in respiration patterns and HRV accompanying Dip & Waves during driving. We found that driving, with or without Dip & Waves, increased heart rate and decreased the time- and frequency-domain indices of HRV. We also found that Dip & Waves during driving did not affect heart rate, but HRV (measured as SDRR and VLF, LF, and HF amplitudes) was greater during the driving periods with Dip & Waves than during the periods without Dip & Waves. On the other hand, we found that although driving had no significant effect on respiratory rate, RRV increased with driving only when Dip & Waves was observed. Furthermore, we observed that while none of the HRV metrics showed significant time dependent trend prior to Dip & Waves, RRV increased progressively from 4 min before Dip & Waves and returned immediately thereafter. Our observations indicate that during driving, the respiratory rate becomes unstable from 4 min before Dip & Waves occurs, while HRV shows no such definite trend. The findings of this study not only show the possibility of smart-shirt sensor as a device to detect driver drowsiness but also suggest that RRV may provide useful clues to predict driver drowsiness, which is unique from those provided by HRV.

Many technologies have been reported to detect car driver drowsiness by biometric sensors [1-3]. In a study using a driving simulator, Awaïs et al. [1] developed models discriminating alert and drowsy states at an
accuracy of 80% from various time- and frequency-domain and complexity metrics of electroencephalogram and HRV using support vector machine. Buendia et al. [2] analyzed the relationship between common HRV indices and subjective sleepiness reported by 76 drivers in real driving situations. They observed that not only HRV indices representing parasympathetic function but also index representing sympathetic function increased with increasing sleepiness level. They hypothesized that the increase in sympathetic function may be due to stress induced by trying to avoid an incident, because the drivers were in real driving situations. In a previous study [4], we found that drowsiness during driving is accompanied by Dip & Waves. Dip & Waves is thought to be a characteristic heart rate pattern that appears when the drivers are drowsy in a situation where they should not sleep.

Most of the methods proposed in earlier studies to detect driver drowsiness use heartbeat interval signals obtained from ECG or other devices [1-4]. Applying these methods to real-world driving situations requires continuous monitoring of the heartbeat intervals in a way that does not burden the drivers, but it is still difficult to record stable ECG signals without attaching skin electrodes or to record a stable pulse wave signals under body movements [5]. Therefore, in order to achieve real-world detection of driver drowsiness, it is important to search for other physiological indicators that can be recorded more easily. In this sense, the use of a respiratory signal, which is easy to detect from outside the body and has a low frequency characteristic requirement, is a strong candidate.

In the present study, we found that RRV increases from 4 min before the appearance of Dip & Waves. Dip & Waves is a surrogate maker of driver drowsiness, and its accuracy has not been established. Thus, it is unclear whether the increase in RRV predicts driver drowsiness or simply the occurrence of Dip & Waves itself. Nevertheless, there may be a possible mechanism that explains why RRV increase prior to the appearance of drowsiness. With falling asleep, the respiratory control mode switches from voluntary mode to involuntary mode, which increases the regularity of the respiratory rate [10]. Before drowsiness occurs, particularly in the situations of fighting drowsiness, the respiratory control mode may cycle back and forth between the voluntary wakefulness mode and the involuntary sleep modes, which may increase RRV. Further researches are needed, however, to directly examine the relationship between changes in respiratory patterns and driver drowsiness.

5. CONCLUSIONS

Our observations suggest that the respiratory signal acquired by the wearable clothing sensor may be used to detect driver drowsiness. An increase in RRV may predict the appearance of drowsiness 4 min before.

REFERENCES

1. Awais, M., Badruddin, N., and Drieberg, M.; A hybrid approach to detect driver drowsiness utilizing physiological signals to improve system performance and wearability, Sensors, 17(9), 2017.
2. Buendia, R., Forcolin, F., Karlsson, J., Sjoqvist, B.A., Anund, A., and Candefjord, S.; Deriving heart rate variability indices from cardiac monitoring – An indicator of driver sleepiness, Traffic Injury Prevention, 20(1), pp.1-6, 2019.
3. Forcolin, F., Buendia, R., Candefjord, S., Karlsson, J., Sjoqvist, B.A., and Anund, A.; Comparison of outlier heartbeat identification and spectral transformation strategies for deriving heart rate variability indices for drivers at different stages of sleepiness, Traffic Injury Prevention, 19(sup1), pp.S112-S119, 2018.
4. Yuda, E., Yoshida, Y., Kawashima, H., Yamamoto, H., Tanaka, H., and Hayano, J.; Hear rate dynamics related to drowsiness, International Behavioral Neuroscience Society (IBNS), 2019.
5. Yuda, E. and Hayano, J.; Non-contact unconstrained continuous pulse wave measurement during long-distance truck operation, Journal of the Operations Research Society of China, in press, 2020.
6. Yuda, E., Yoshida, Y., Kawashima, H., Yamamoto, H., Tanaka, H., and Hayano, J.; Physiological mechanisms of Dip & Waves of heart rate: Polysomnographic analysis during maintenance of wakefulness test, The 2018 JSAE Congress (Autumn), p.108, 2018.
7. Corey, T.P., Shoup-Knox, M.L., Gordis, E.B., and Gallup, Jr., G.G.; Changes in Physiology before, during, and after Yawning, Frontiers in Evolutionary Neuroscience, 3, p.7, 2011.
8. Hayano, J., et al.; Continuous assessment of hemodynamic control by complex demodulation of cardiovascular variability, The American Journal of Physiology, 264, pp.H1229-H1238, 1993.
9. Hayano, J., et al.; Assessment of frequency shifts in R-R interval variability and respiration with complex demodulation, Journal of Applied Physiology, 77(6), pp.2879-2888, 1994.
10. Hayano, J., Ueda, N., Kisohara, M., Yoshida, Y., Tanaka, H., and Yuda, E.; Non-REM sleep marker for wearable monitoring: Power concentration of respiratory heart rate fluctuation, Applied Sciences, 10(9), 3336, pp.1-12, 2020.

Emi YUDA (Member)
Emi Yuda was born in Tokyo, Japan in 1980. She studied informatics at M.V. Lomonosov Moscow State University until 2003 and then received an M.S. degree from Tsukuba University, Japan. She received a Ph.D. from Nihon University in 2019. From 2013 to 2014 she was a research assistant at Santa Monica College in California, USA. From 2015 to 2019, she was a NEDO project researcher at Nagoya City University Graduate School of Medical Sciences. Since 2019, she has been an assistant professor at Tohoku University Graduate School of Engineering. Her current research is Medical Informatics and Data Science. She has many achievements in the field of Informatics and Big Data.

Yutaka YOSHIDA (Non-member)
Yutaka Yoshida studied the business administration and computer science at Aichi Institute of Technology and received Ph.D. degree in 2008. He was a project researcher at Knowledge Hub of Aichi from 2011 to 2015 and was a researcher at Nagoya City University Graduate School of Medical Sciences from 2016 to 2017. Since 2018, he has been a researcher at Nagoya City University Graduate School of Design and Architecture. His specialized field is biological information engineering, signal processing and ergonomics. He received the paper award at the Japan Society of Neurovegetative Research in 2005 and 2007.

Junichiro HAYANO (Non-member)
Junichiro Hayano graduated Nagoya City University Medical School, Nagoya, Japan and received an M.D. degree in 1980. From 1981 to 1983, he received residency training in psychosomatic medicine at Kyushu University School of Medicine, Japan. He obtained a Ph.D. degree (Dr. of Medical Science) in 1988 from Nagoya City University Graduate School of Medical Sciences. From 1990 to 1991, he was working as a visiting associate at the Behavioral Medicine Research Center, Duke University Medical Center, Durham, NC, USA. In 1984, he got a faculty position at Nagoya City University Medical School and has been a Professor of Medicine at Nagoya City University Graduate School of Medical Sciences since 2003.