1. INTRODUCTION

The development of technology for estimating the emotions of workers using objective biometric indicators is expected to provide useful information for improving work efficiency and safety, preventing job separation due to work stress, and managing occupational health. In the last decade, several efforts have tried to develop the methods to identify the types of emotion from physiological signals including electroencephalogram (EEG), electrodermal activity, electrocardiogram (ECG), pulse wave, respiration, and eye-movement [1-15]. However, there are many issues in estimating emotions in the workplace from these signals.

EEG may be the most promising signal for this purpose because emotions occur in the brain, including the cerebral cortex [7-10, 15], but the requirements for scalp electrodes for EEG measurements interfere with daily use for monitoring in the workplace. Evidence has accumulated for the usefulness of heart rate variability (HRV) and nonlinear heart rate dynamics analyzed from ECG to estimate emotions [3,10,11,14,15], but the need for skin electrodes for ECG makes frequent long-term monitoring difficult. Pulse rate variability (PRV) analyzed from pulse wave signals obtained by a photo-plethysmograph (PPG) sensor has been proposed as a potential surrogate of HRV. Although the pulse rate calculated from pulse wave generally matches well with the heart rate from ECG, the power spectrum of the PRV does not match the power spectrum of the HRV analyzed from the simultaneously measured ECG and, even when HRV does not exist, PRV does exist [16,17]. Additionally, power spectrum of PRV could differ depending on the measurement site [18]. PRV may provide useful features for estimating emotions [1,3,6], but interpretations of the associations of PRV with emotions cannot be referenced from those of HRV. Finally, the higher the number of signal modality, the better the accuracy of emotion estimation [3,6,10,14,15], but at the expense of ease of use in the workplace.

In response to these needs, we have been working on a project to develop methods for estimating the emotions of office workers from information obtained from a single wearable sensor [19, 20]. In a previous study of five healthy office workers, we analyzed the relationships between biometric information obtained from a watch device and self-reported strongly conscious emotions during working hours [19]. We found that the type of emotion can be developed on the plane consisting of two coordinates regressed by the biometric information and that the coordinates were similar to arousal and valence axes of the Russel’s Circumplex model of affect [21]. However, the previous study had a small sample size (n=5),
total monitoring period was 173 days, and during which only 161 out of 388 strongly conscious emotions were able to be analyzed.

The present study was therefore performed to confirm the previous findings. We increased the number of subjects and monitoring period. Furthermore, we added new indices reflecting the stability of PRV-derived respiratory frequency which may change with emotional states. We also adopted a new emotion-type estimation method that directly estimates the arousal and valence axis values based on the Russel’s Circumplex model. A part of this study has been published as the proceeding of the 6th International Symposium on Affective Science and Engineering (ISASE 2020) [22].

2. METHODS

2.1 Subjects

Subjects were 11 healthy office workers (10 males and 1 female) in a company. They participated in this study between November 2017 and December 2018. The data were provided to the researchers after being anonymized for name and age by the company. The protocol of this study has been approved by the Ethics Review Committee of Nagoya City University Graduate School of Medical Sciences and Nagoya City University Hospital (No. 60-18-0211).

2.2 Protocols

Subjects wore a bracelet-shape biometric sensor (Silmee W20, TDK Co., Japan) between 08:30 and 21:30 every day except holidays during the experimental period. The wearable device sized about 20.5×65.0×12.5 mm (the thickest part) and weighted about 29.5 g. It equipped with a built-in PPG sensor and sensors for acceleration, temperature, ultraviolet light, and sound, by which it detected continuously beat-to-beat pulse intervals (PI), physical activity (level and kind), skin temperature, environmental ultraviolet, and the periods of conversation and sleep. During the measurement, subjects were instructed to record the labels of strongly conscious emotions (happy, angry, relaxed, and sad) every 30 min when feeling strong emotions.

2.3 Data Analysis

The time series of beat-to-beat PI were preprocessed to detect the periods of noise and data defect using custom software. Then, the frequencies and amplitudes of very-low frequency (VLF, 0.0033–0.04 Hz), low-frequency (LF, 0.04–0.15 Hz), and high-frequency (HF, 0.04–0.45 Hz) components of PRV were continuously measured as the functions of time by the method of complex demodulation [23,24]. The amplitudes of PRV frequency component were averaged over every 30 min synchronized with the time frame of emotion label and the standard deviations (SDs) of VLF, LF, and HF amplitudes were calculated for the same time frame. To evaluate the amplitude fluctuation of PRV components, the ratio (%) of the amplitude SD of each frequency component to the mean amplitudes of the corresponding component was calculated as the amplitude coefficient of variation (VLFcv, LFcv, and HFcv).

Additionally, to estimate the respiratory frequency instability, frequency variability of respiratory component of PRV was analyzed. For this purpose, PRV power spectra were calculated for 5-min windows shifting with a step of 1 min. The frequency of the highest spectral peak between 0.15 and 0.45 Hz was determined in each spectrum as an estimate of respiratory frequency, yielding time series of estimated respiratory frequency at 1-min interval. Then, the respiratory frequency time series were moving averaged with 5-min window width (5 data points) and the percent deviations of original respiratory frequency from the moving average were calculated with 1 min interval. This value was named frequency variability of respiratory sinus arrhythmia (fvRSA), because the frequency of respiratory PRV component in a 5-min window is thought to reflect the frequency of respiratory sinus arrhythmia even considering the variations in phase between PI and R-R interval of ECG. The percent deviation was averaged over the 30-min time frame of the emotion label.

2.4 Statistical Analysis

Statistical Analysis System (SAS Institute, Cary, NC) was used. To extract biometric information associated with emotion type, the emotion labels were converted into x and y coordinates reflecting valence and arousal, respectively, of the Russel’s Circumplex model, i.e., happy, angry, relaxed, sad, and no-label (control) as (1, 1), (-1, 1), (1, -1), (-1, -1), and (0, 0), respectively. Then, biometric measures that explained x and y coordinates were extracted by SAS regression procedure with stepwise variable selection method. The performance of regression models to discriminate between high and low valence (happy-relaxed vs angry-sad) and between (high and low arousal (happy-angry vs relaxed-sad)) were evaluated by receiver-operation characteristic curve analysis. Statistical significance was considered when P value <0.05.
3. RESULTS

3.1 Associations between emotion type and biometric indices

From a total of 911 days of records in the 11 subjects, a total of 9,737 hours of data were obtained. During the monitoring, a total of 954 self-reported emotion labels were obtained, 470 of which were obtained with simultaneous recording of PI that could be analyzed for PRV.

Figure 1 shows the univariate associations between emotion type and PRV indices. HF amplitude and HFcv of PRV increased with anger and sadness. LF/HF increased with relax. Anger tended to associate with an increase in fvRSA.

Figure 2 shows the univariate associations between emotion type and other biometric indices. Skin temperature increased with happiness and relax and decreased with anger and sadness. Conversation time was longer when reported happiness and anger than when reported as relax and sadness.

3.2 Biometric indices explaining valence and arousal axes

By stepwise regression analyses, HFcv and skin temperature were extracted as the best variable combination explaining the valence axis values composed of emotion labels. The ROC curve revealed that the model discriminated between high valence (happiness and relax) and low valence (angry and sadness) states with an AUC of 0.64 ($P = 0.0001$). On the other hand, fvRSA and conversation time were extracted as the best variable combination explaining the arousal axis values.

PR = pulse rate, SDPI = standard deviation of pulse interval, VLF = very-low-frequency amplitude, LF = low-frequency amplitude, HF = high-frequency amplitude; fRSA = frequency of respiratory sinus arrhythmia estimated from PRV, LF/HF = LF-to-HF ratio in power, HF freq = frequency of HF component, VLFcv = coefficient of variation of VLF amplitude, LFcv = coefficient of variation of LF amplitude, HFcv = coefficient of variation of HF amplitude, fvRSA = frequency variability of respiratory sinus arrhythmia estimated from PRV

Figure 1: Univariate associations between pulse rate variability (PRV) indices and emotional labels

Figure 2: Univariate associations between other biometric signals and emotional labels
model discriminated between high arousal (happiness and angry) and low arousal (relax and sadness) states with an AUC of 0.61 ($P = 0.001$).

Figure 3 shows the distributions (means and standard errors) of valence and arousal axes values calculated from these regression models for each emotion type.

4. DISCUSSIONS

We developed a model that estimates the emotions of office workers using information obtained by a single wearable biometric sensor. We analyzed 9,737 hours of biometric signals together with strongly conscious emotions collected for 11 healthy office workers. The emotion types were converted into two coordination values for valence and arousal and were separately regressed by the biometric signals. The valence axis was best regressed by the combination of HFcv and skin temperature and the arousal axis were best regressed by the combination of fvRSA and conversation time. As the results, four emotion types (happiness, anger, relaxation, sadness) were separated into four quadrants consisting of these biometric signals.

In this study, we observed the association between skin temperature and higher valence and between conversation time and higher arousal. To our knowledge, these findings have not been reported in earlier studies of emotional estimation using biometric indicators. Because skin temperature and conversation time are indexes that can be easily measured by wearable sensors, they have a great potential as future indexes for emotion estimation.

The present study has important limitations and much room for improvement. As expected, the valence and arousal axis values estimated by biometric signals showed significant discriminant power between happiness-relax and anger-sadness and between happiness-anger and relax-sadness, respectively. However, the discriminant accuracy for the classification of four emotion types was modest. Further refinements of the model are needed in the future studies. Additionally, this study was performed in office workers working mostly indoor. Although skin temperature and conversation time were extracted as explanatory variables of valence and arousal, respectively, these signals could not be used in hot or cold environments or in other workplace where conversation is restricted.

This research project has been implemented to be used for workers’ emotion estimation to improve work efficiency and safety, prevent work separation due to work stress, and manage occupational health. The results of this research, however, may have broad utility beyond pressure, pulse conduction time, peripheral vascular dynamic compliance, capillary, blood flow, and venous pressure by respiration and other factors [17]. As the result, frequency components of PRV are observed even in patients with an implanted cardiac pacemaker with a fixed ventricular rate [16, 17]. Furthermore, PRV obtained at the wrist by PPG sensors may be influenced by wrist movement artifacts. Consequently, PRV could provide paradoxical results such as greater HF amplitude during light physical activity than during dozing [20]. In this study, we observed a low HF amplitude with relax (Figure 1), which is inconsistent with the concept that HF amplitude of HRV reflect cardiac parasympathetic function [25], suggesting the danger of easy application of the knowledge obtained from HRV to PRV.

In this study, we also observed the associations of HFcv with lower valence and of fvRSA with higher arousal. HFcv may reflect intermittent wrist movements accompanying increased irritability. The other hand, fvRSA reflects the instability of respiratory frequency. Because the respiratory frequency is stabilized during NREM sleep [26, 27], it seems reasonable that fvRSA increased with arousal level (anger and happiness).

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the originally intended purpose. With the rapid penetration of artificial intelligence into everyday life and the workplace, the ability to infer human emotions may become an essential ability of artificial intelligence with “humanity.”

5. CONCLUSIONS

Our findings suggest that among office workers, physiological features necessary to compose the valence and arousal axes of theRussell’s Circumplex model of affect may be obtained by a single wearable sensor.

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