Emotion and Fatigue Monitoring Using Wearable Devices

Jong-Seok Lee[1], You-Suk Bae[2], Wongok Lee[2], Hyunsuk Lee[2(✉)], Jinkeun Yu[2], and Jong-Pil Choi[3]

[1] School of Integrated Technology Yonsei University, 85, Songdogwahak-ro, Yeonsu-gu, Incheon, Korea
jong-seok.lee@yonsei.ac.kr

[2] Clart Co., LTD, 250, Hagui-ro, Dongan-gu, Anyang-si, Gyeonggi-do, Korea
{ysbae,goks.lee,leehs,yjk760}@clart.kr

[3] Department of Computer Engineering, Korea Polytechnic University, 237, Sangidaehak-ro, Siheung-si, Gyeonggi-do, Korea
jpchoi@kpu.ac.kr

Abstract. This paper presents our prototype wearable system for monitoring emotion and fatigue of users. We develop a hardware part that can measure Galvanic skin response and photoplethysmography at a sampling rate of 100 Hz. In addition, we build a classification module that can distinguish the type of emotion and the level of fatigue of the user based on the measured signals. It is demonstrated that the developed system can successfully be used for emotion and fatigue monitoring.

Keywords: Galvanic skin response · Photoplethysmography · Classification Neural networks

1 Introduction

With the advances in wearable devices such as smart bands, it has become possible to constantly monitor users' mental and physical states and provide feedbacks based on the sensed states [1]. In particular, physiological channels such as heart rate, Galvanic skin response (GSR), and skin temperature provide useful information regarding the user's state. Promising applications include health monitoring, stress management, content recommendation, etc. For instance, if the level of fatigue detected by a smart band is too high during driving, some rest or sleep can be suggested; if the user is found to be depressed by a smart band, some joyful movies can be recommended to change the user's mood.

In this paper, we concentrate on developing a prototype wearable system for emotion and fatigue monitoring. It measures the GSR and photoplethysmography (PPG) signals of the user and perform recognition of the emotion type and level of fatigue. We develop a hardware prototype equipped with the sensors. And, we design a software-based recognition part that analyzes the signals and conducts classification using neural networks.

S. O. Hwang et al. (Eds.): ICGHIT 2018, LNEE 502, pp. 91–96, 2019.
https://doi.org/10.1007/978-981-13-0311-1_17

The remainder of the paper is organized as follows. Section 2 describes the hardware prototype. In Sect. 3, the recognition system is explained including data collection, feature extraction, and classifier design. The experimental results are presented in Sect. 4. Finally, conclusion is given in Sect. 5.

2 Hardware

We develop a prototype circuit board that can be integrated in a wearable device to measure physiological responses of the user. In particular, a GSR sensor module and a PPG sensor module are included. Besides, our prototype also equips a microcontroller unit (MCU), a power supply module, a USB communication module, and a Bluetooth communication module. A maximum sampling frequency of 1000 Hz is supported.

Figure 1 shows a user's hand connected with the developed sensor board. In Fig. 2, example GSR and PPG signals collected using the board are shown.

Fig. 1. Developed system attached to a hand.

3 Recognition System

3.1 Data Collection

Ten subjects were employed for data collection. Each subject took part in eight sessions held in different days. In each session, the experimental procedure is as follows. First, the objective and procedure of the experiment were explained. Then, the GSR and PPG sensors were placed at a hand of the subject sitting on a chair. The subject was instructed to relax for five minutes, during which the GSR and PPG signals for the resting state were recorded. After an additional rest period of three minutes, three music videos were played to induce particular emotional states, i.e., joy, anger, and sadness, respectively, during which the GSR and PPG signals were recorded. After the end of a music video and before the start of another, a break for three minutes was given to allow the subject's emotional state to revert to a normal state. The subject wore an earphone to listen to music, so that any environmental noise did not interrupt the

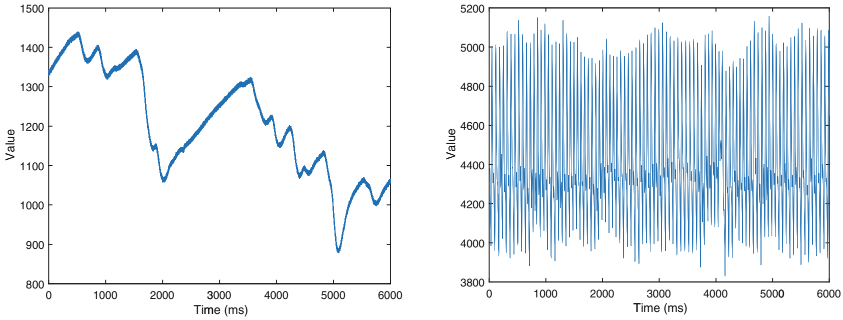

Fig. 2. Example GSR (left) and PPG (right).

subject's immersion to the stimuli and induction of emotional arousal. In the whole experiment, a specific music video was shown only one time.

In each session, the subject was asked to rate the level of fatigue in the Likert scale ranging from 1 (not tired at all) to 9 (extremely tired).

The physiological signals were recorded at a sampling frequency of 100 Hz.

3.2 Feature Extraction

First, the original signals were down-sampled to 10 Hz. Then, each signal was divided into segments by using a window having a length of 60 s and moving 5 s at a time. Each segment becomes a data point in classification.

For each segment, we extract seven features from GSR, and five features from PPG, which have been known to be effective for physiological signal analysis [2–4]. It should be noted that in literature, there are abundant types of features that can be extracted from GSR and PPG, but due to the limit set by the hardware specification, we had to choose the most effective features among them.

The seven GSR features are as follows:

- Average value of the signal
- Standard deviation value of the signal
- Average value of the derivative of the signal
- Standard deviation value of the derivative of the signal
- Average value of the signal after low-pass filtering with a cut-off frequency of 0.2 Hz
- Average value of the derivative of the signal after low-pass filtering with a cut-off frequency of 0.2 Hz
- Number of peaks in the signal after low-pass filtering with a cut-off frequency of 0.2 Hz

The five PPG features are as follows:

- Average height of the peaks in the signal
- Standard deviation value of the height of the peaks in the signal
- Heart rate

- Standard deviation value of the peak-to-peak intervals
- Average value of the squared heart rate variability

3.3 Classification

The emotion classification task is defined to recognize the given signal as one of the four classes, i.e., neutralness, joy, anger, and sadness. The four classes of the fatigue level classification task correspond to 1 and 2, 3 and 4, 5 and 6, and 7 and 8 in the rating scale. Note that score 9 was never given by the subjects, therefore it was not considered in the classification.

Two classification schemes are tested, namely, the subject-wise scheme and the subject-dependent scheme. In the subject-wise scheme, a separate classifier is built for each subject, where the first half of the signal is used for training and the remaining half for testing. The average classification performance over all subjects is reported. In the subject-dependent scheme, a classifier is constructed using the first half of the signals of all subjects and tested using the remaining data of all subjects.

We use multilayer neural networks having one hidden layers as classifiers. We try various numbers of hidden neurons to examine the performance with respect to the neural network complexity. A sigmoid function is used as the activation function of each hidden neuron. The neural networks are trained using the Levenberg-Marquardt algorithm that is one of the fastest neural network training algorithms. The maximum training epoch is set to 200.

4 Results

Figure 3 shows the classification performance for the subject-wise scheme. The emotion classification accuracy reaches the best (61.9%) when 50 hidden neurons are used, while the fatigue classification accuracy is the highest (88.2%) when the number of hidden neurons is 40. It is observed that the performance becomes saturated once a sufficient number of hidden neurons is used.

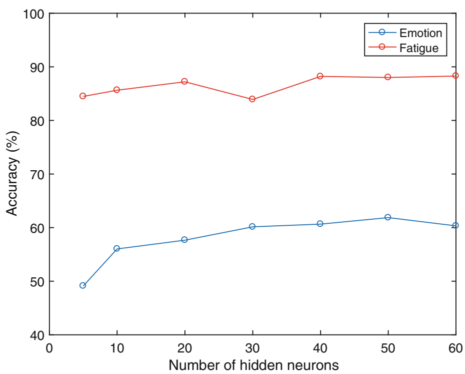

Fig. 3. Performance of subject-wise classification for emotion and fatigue

In Fig. 4, subject-dependent classification performance is depicted. It is observed that the accuracy in this figure is lower than that in Fig. 3, which is due to the subject-wise variation of the patterns appearing in the physiological signal. The best performance is obtained when the number of hidden neurons is 50 for emotion (48.4%) and 50 for fatigue (71.2%).

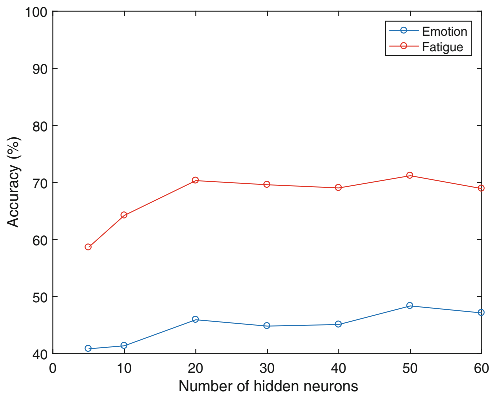

Fig. 4. Performance of subject-dependent classification for emotion and fatigue

5 Conclusion

In this paper, we have presented our prototype system for emotion and fatigue monitoring. Through an experiment, it was shown that the hardware and software parts can monitor the type of emotion and the level of fatigue with a satisfactory accuracy.

The results showed that user-dependent variation can be a source of performance degradation. In the future, therefore, it will be desirable to focus on reducing the effect of such user-dependent variation in order to make the system work robustly across different users.

Acknowledgment. This work was supported by the Technology Innovation Program (10052841, "Development of stretchable smart band for young people") funded by the Ministry of Trade, Industry and Energy, Korea.

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