Emotion estimation by acceleration pulse wave analysis

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Abstract: The prevalence of mood disorders is increasing worldwide, making mental health self-care necessary. One possible solution to address this need is the use of wearable technology that monitors and records moods. In this study, we attempted to (1) estimate the emotional states of joy, anger, and neutral from blood volume pulse intervals and (2) evaluate the potential applicability of blood volume pulse-based mood mapping in wearable devices. The pulse wave data available on the Massachusetts Institute of Technology (MIT) Affective Computing Group website were used. Acceleration pulse waves were analyzed using second-order differential calculus. Mean NN interval, standard deviation of NN intervals, and coefficient of variation of RR intervals were analyzed as emotional features, based on which a three-state classification model was created via linear discriminant analysis. The classification accuracy at the pulse wave measurement time of 30 seconds was 57%, whereas that at 100 seconds was 53%. Our findings indicate that mood estimation using acceleration pulse wave analysis has potential application in wearable technology for mental health self-care and warrant further research to strengthen the data.

Keywords: Emotion, Acceleration pulse wave, meanNN, SDNN, CVRR

1. INTRODUCTION

The Ministry of Health, Labor and Welfare of Japan [1] has identified that mood disorders, including depression, are increasing annually in the country. The number of individuals affected by mood disorders has increased from 1.116 million in 2011 to 1.276 million in 2017. In total, 5.7% of the population suffer from depression at least once in their lifetime, and 30.3% of patients would visit a medical institution within 12 months [2]. Many patients are not adequately treated for depression. In addition, not all patients with mood disorders can decide for themselves whether to consult a medical practitioner. Therefore, some patients with depression would rely on mental health self-care using such interventions as wearable technology.

Recently developed wearable devices are equipped with pulse wave measurement sensors that allow users to objectively predict their mood based on their heart rate. As heart rate and its fluctuations represent autonomic nervous system activity, the mean NN interval (meanNN), standard deviation of NN interval (SDNN), and coefficient of variation of RR intervals (CVRR) serve as key features of moods. A statistical model with these characteristics as explanatory variables and mood introspection as the objective variable could be created. In 2018, Yamada [3] constructed a stress classification model with 63% accuracy based on low-frequency heart rate variability and respiratory rate variability using a support vector machine. Although a number of studies have estimated psychological states from heart rate variability, further research in incorporating this parameter in wearable technology is needed. We speculated that the choice of epoch time for continuous pulse waves has to be verified by simulation. Therefore, in this study, we used emotion-labeled pulse wave datasets from the Massachusetts Institute of Technology (MIT) Affective Computing Group website to validate emotion classification at measurement times of 30 and 100 seconds.

2. METHODS

2.1. Acceleration pulse wave and peak detection

The emotional datasets published by the MIT Affective Computing Group [4] on their website are based on eight emotional states (anger, grief, hate, joy, reverence, love, romantic love, and neutral) and four physiological signals that were observed and measured in one subject for 20 days [5]. In this study, blood volume pulse (BVP) was used according to the group’s data usage rules [4], measured by backscatter photoplethysmography, and sampled at 20 Hz [6]. We then focused on the anger, joy, and neutral datasets.

Figure 1a shows the raw waveform of BVP signals, whereas Figure 2b shows their acceleration pulse waveform. The BVP waveform was converted into an acceleration waveform using the second-order differential method, and the peak of the pulse waves became

![Figure 1: Blood volume pulse (BVP) waves as analyzed by second-order differentiation. (a) Raw BVP waveform. (b) Acceleration pulse waveform.](image-url)
ame clear. The peak was positively and negatively inverted by second-order differential calculus, but the intervals were maintained [7]. The peak search was determined using the threshold method. Panels (a)–(c) of Figure 2 show the 30-second epoch acceleration pulse waves for anger, joy, and neutral, respectively, and panels (d)–(f) of the same figure show the corresponding 100-second epoch acceleration pulse waves. The 30-second epoch served as the start data for the 100-second epoch, and although it covered a shorter measurement time than the latter epoch, it yielded approximately a third of the pulse wave peaks.

These signal processes were calculated using MATLAB [Natick, USA].

2.2 Extraction of emotional features
MeanNN, SDNN, and CVRR were calculated from the peak time intervals of the pulse waves. Feelings of excitement and stress were determined to shorten meanNN because they increased the heart rate. In addition, reduced heart rate fluctuations lowered SDNN. In the resting state, meanNN and SDNN increased. CVRR, which is a standardized heart rate interval deviation, was derived from meanNN and SDNN as shown in Equation (1):

$$\text{CVRR} = \frac{\text{SDNN}}{\text{meanNN}} \times 100(\%) \quad (1)$$

2.3 Emotion classification by linear discriminant analysis
We created a linear discriminant analysis (LDA) classifier and attempted to categorize the three emotional states of joy, anger, and neutral. The general LDA discriminant Z score was calculated as shown in Equation (2), where the W coefficient is obtained from the training data, X represents the test data, and Z is determined as either >0 or <0. Multiple expressions are combined to determine the score for multiple emotions. In this study, the LDA model was constructed with the fitcdiscr function of MATLAB: 3 emotions \times 3 features \times 20 days = 180 data size. In total, 60 data points per emotion, which were divided into training data and test data, were used in this simulation. The two categories were further divided into three patterns, namely, 30:30, 45:15, and 58:2.

$$Z = W_1X_1 + W_2X_2 + W_3X_3 + \cdots + W_nX_n + a_0 \quad (a_0: \text{constant}) \quad (2)$$

3. EPOCH TIMES AND CLASSIFICATION RATES
Tables 1 and 2 show the classification results for the 30-second epoch (training data/test data = 30:30) and 100-second epoch (30:30), respectively. Neutral, anger, and joy each had 10 test data cases. Table 1 also shows that the 10 neutral data cases were distributed among the

Figure 2: Acceleration pulse waves for the anger, joy, and neutral emotional states in the (a–c) 30-second epoch and (d–f) 100-second epoch. Open circles mark peaks of pulse; vertical bars, intervals of pulses.
neutral category with 3 data cases, anger category with 1 data case, and joy category with 6 data cases. A higher value in the diagonal matrix indicated better classification accuracy. Comparison of the data in Table 1 with those in Table 2 revealed that the 100-second epoch estimated the neutral (7/10 cases) and anger (7/10 cases) emotional states well. 

Figures 3 and 4 illustrate the relationship between the number of training data points and the classification rate for the 30-second epoch and that for the 100-second epoch, respectively. In the 30-second epoch (Figure 3), the classification accuracy levels for anger and neutral were noted to improve when the number of training data points was 58. In the 100-second epoch (Figure 4), the classification rates for anger and neutral were observed to improve when the number of training data points was 30. The simulation had limited conditions; however, the classification accuracy levels for anger and neutral could be improved to approximately 60–70% by increasing the number of training data points in the 30-second epoch and to approximately 70% even with a low number of training data points in the 100-second epoch.

### Table 1: Classification scores in the 30-second epoch

| OUTPUT | Neutral | Anger | Joy |
|--------|---------|-------|-----|
| Neutral| 3.      | 1.5   | 6.  |
| Anger  | 0.5     | 3.5   | 5.5 |
| Joy    | 3.5     | 1.    | 6.5 |

### Table 2: Classification scores in the 100-second epoch

| OUTPUT | Neutral | Anger | Joy |
|--------|---------|-------|-----|
| Neutral| 7.5     | 1.5   | 3.5 |
| Anger  | 0.5     | 7.5   | 3.5 |
| Joy    | 9.5     | 0.5   | 1.5 |

### Figure 3:
Classification rates in the 30-second epoch. Training data/test data = 30:30, 45:15, and 58:2.

### Figure 4:
Classification rates in the 100-second epoch. Training data/test data = 30:30, 45:15 and 58:2.

4. **SUMMARY**

In this study, we have examined the potential applicability of pulse wave emotion classification in wearable technology designed to monitor and record moods. We compared emotion classification rates between short (30 seconds) and long (100 seconds) measurement times by simulation using the anger, joy, and neutral datasets published online by the MIT Affective Computing Group. Based on this simulation, in the case of the 30-second epoch, 60–70% classification accuracy was obtained by using most of the acquired data (58/60 cases). On the other hand, in the case of the 100-second epoch, 70% classification accuracy was obtained for half of the training data (30/60 cases). These findings indicate that prediction of anger and neutral emotional states could be of value in wearable technology for mental health self-care. However, as this study was based on data verified for one subject only and operated under limited conditions, whether the linear discriminant learner can classify pulse wave features for individual users needs to be further tested. In addition, it must be implemented on the Android or iOS platform in order to validate the features in a wearable state.
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