Emotion Recognition Using Biological Signal in Intelligent Space

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Abstract. In this study, we focus on emotion recognition for service robots in the living space based on Electrocardiogram (ECG). An emotional state is important information that allows a robot system to provide appropriate services in way that are more in tune with users' needs and preferences. Moreover, the users' emotional state can be feedbacks to evaluate user's level of satisfaction in the services. We apply a diagnosis method that uses both inter-beat and within-beat features of ECG. The post hoc tests in Analysis of Variance (ANOVA) showed that our approach satisfies more confidence level of difference between emotions than conventional methods. Our system design was based on wireless and wearable biological sensor for mobility and convenience of users' daily lifestyle.

Keywords: Emotion Recognition, ECG, Intelligent Space.

1 Introduction

In order to provide a suitable service to a user, computers should be more intelligent and more like human beings. Also, they should be able to understand what users feel.

In emotion recognition, we focus on a biological approach that has advantages over other approaches because people's emotions vary in different ways according to environment, culture, education and so on. However, people's emotions are very similar in terms of biological signals. People can hide their emotions from outside appearances but they cannot hide their emotions in biological signals. Biological sensors can solve a limitation of the visual technique that requires a frontal view and clear face to detect expressions. In addition many researchers tried to decrease size of biological sensors for using in health care monitoring. This improvement makes the sensors suitable for our system because it is small enough to be use without any interference to daily life.

Different emotional expressions produce different changes in ANS activity [1]. Paul Ekman et.al found in their experiments that heart rate increased more in anger and fear than in happiness. The main limitation of emotion recognition by using only ECG signals is it can categorize emotion into a few categories such as positive/

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negative feeling [2,3,4], feeling of being stressed/relaxed [5,6], or fear/ neutrality [7]. Some studies (e.g., [8,9,10,11]) overcome this limitation by combined ECG with other physiological signals that are related with organs that affected by the ANS as showed in table 1. Among these studies, some correlates between emotion and ECG could be identified: increase of heart rate associated with fear (e.g. [9]) and anger (e.g., [8]), increase of heart rate variability associated with stress (e.g. [6]). However some results were controversial: sadness has been found to sometimes lead to an increase (e.g., [12]) and sometimes lead to a decrease (e.g., [9]) of heart rate.

These previous studies extracted only inter-beat information of ECG such as RR-interval or heart rate (HR) time series. Some researches use statistical data of this information (min, max, average, standard deviation of normal-to-normal of R-R intervals (SDNN), Root Mean Square of Successive Different of RR intervals (RMSSD), and heart rate variability (HRV)) in order to maximize efficiency of ECG. We proposed to use ECG's inter-beat features together with within-beat features in our recognition system which we will be describing detail in the next section.

2 Methodology

2.1 System Structured Environment in Intelligent Space

In this system we observed a person in the wide area living space as shown in figure 1. A user wore the RF-ECG that collected data from the movement of the heart's index and sent it to a base station that was connected to a personal computer (PC). This system was designed to be mobile that provided the user more freedom to move while the system monitored the person continuously.

2.2 Wireless ECG Sensor (RF-ECG)

The sensor is selected based on three important criteria. The first criterion was that its signal had to be strongly related with the human emotion. The second criterion was that the sensor had to adhere to human skin without discomfort. The last criterion was

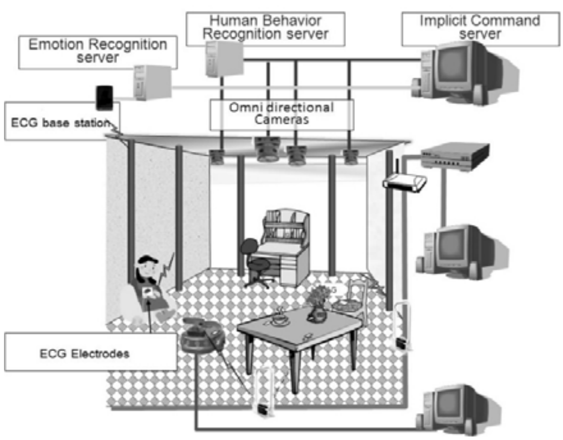

Fig. 1. Structured Environment in Intelligent Space

that the sensor has to be wearable and convenient for use in normal daily life. In this study, the RF-ECG biosensor kit that enables wireless medical monitoring was selected as shown in figure 2. This sensor can record and wirelessly transmit ECG signals to the server with 204 Hz. The sensor utilizes low power consumption RF transmission, which purportedly enables it to broadcast a constant signal for up to 48 hours on a single charge. The sensor used in this study was a low weight (12 g) and small size sensor (40 mm x 35 mm x 7.2 mm). The wireless RF transmitter had an open area range of up to 15 m as shown in table 1.

Table 1. Specification of the RF-ECG monitoring devices

Features	***Specification***
Size and shape	40mm x 35mm x7.2 mm
Material	ABS resin (plastic)
Wireless type	Advanced 2.4 G and Low Band Power Data Comunication
Transmit power	1 mW (0dbm)
Transfer rate	1 Mbps
Protocal	CRC with a proprietary
Current consumption	2-2.4 mA
Distance	Approximately 15 m
Up time	48 hours
Low-frequency cutoff	0.05 Hz - 0.32 Hz
Sampling rate	204 Hz, 102 Hz
High-frequency cutoff	100 Hz

2.3 Emotion Recognition

ECG signal was sampled with a sampling frequency of 204 Hz. Then digital signal was transmitted wirelessly to the server as shown in figure 2.

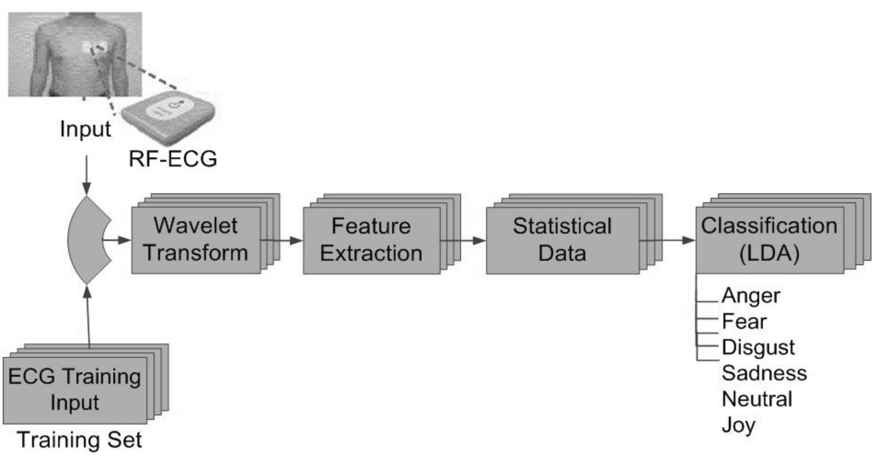

Fig. 2. Emotion recognition by using RF-ECG sensor

Annotation of the ECG (Wavelet Transform). The continuous wavelet transforms (CWT) and fast wavelet transforms (FWT) were used for automatic annotation of the ECG cardio cycle[old8]. The annotation method consists of two phases: QRS detection followed by P, T wave location.

- QRS detection: To amplify the QRS complex and separate low frequency (P and T waves) and high frequency (noise), the CWT transform is applied at 12Hz with an inverse wavelet. The CWT spectrum obtained is further filtered with FWT using an interpolation filter to remove frequency content below 30Hz and the rest of the spectrum is denoised with a hard threshold using a MINIMAX estimate. The reconstructed ECG signal after denoising contains only spikes with nonzero values at the location of the QRS complexes.
- P, T waves detection: After QRS complexes are detected the intervals between them are processed for detection of P and T waves.

Feature extraction. After we located the location of each wave on ECGs, several parameters that indicate each part of heart's activity were calculated. In this process, we calculate not only inter-beat information of ECG (RR-interval or HR) but also within-beat information of ECG (PR, QRS, ST, QT intervals, PR, and ST segments).

Statistical data. To prevent data loss and reduce the number of the features, we used the statistic data (mean, and standard deviation) of each parameter to be the features. Note: there are two types of standard deviation between heart beats (SDNN and RMSSD).

Different people have different biological signals. To avoid this effect, each feature (HR, SDNN, RMSSD, QT, STDEV(QT), PR, STDEV(PR), STDEV(QRS), ST, STDEV(ST)) was normalized by subtracting each parameters from its mean in the neutral emotion.

Classification. Linear Discriminant Analysis (LDA), and Adaptable K-Nearest Neighbor(A-KNN)[13] are used to classify emotion into six categories(anger, fear, disgust, sadness, neutral, and joy). To evaluate the recognition performances, we separate data into two set. There are 147 data for training and 147 data for testing.

3 Experiments

3.1 Picture Database

Our experiments were based on International affective picture system (IAPS) database [old10] that contained 20 sets of 60 pictures. Each picture induced a variety of emotion and has pre-rated of emotion. In experiment, we selected 60 pictures.

3.2 Participants

This study was conducted with 6 subjects, including 5 healthy males (mean±SD age = 27.2±3.63 years) and one female (age =33). We didn't examine many subjects since each subject was recorded with 60 ECG signals. The total number of samples was 360(6x60) samples that was sufficient.

3.3 Data Collection

In the experiments, we applied the same process with IAPS experiments. However, we changed from pencil-paper based to computer based for questionnaire section to reduce the effort for management of questionnaires. We provided the same questionnaires to the all subjects. When the subjects did not feel emotions promptly in IAPS, we did not apply the data to an experiment. In the experiment, we showed 60 pictures to the subjects one by one. Each trial began with a preparation step to train the subjects to familiar with and understand the experiment. We attached ECG electrodes on the subject's chest. The picture to be rated was presented for 6 seconds, and immediately after the picture left the screen, the subject made their ratings. A standard 15 seconds rating period was used, which allowed ample time for the subjects to finish the questionnaire. We started to measure the ECG signal at the same time the first picture was presented, so we were able to separate the ECG signal into 6 second of 60 signals per subject.

4 Results and Discussions

4.1 Post Hoc Tests in Analysis of Variance (ANOVA)

The Least Significant Difference (LSD) test was used to explore all possible pair-wise comparisons of means comprising an emotion factor using the equivalent of multiple t-tests. In this section, we compare two techniques.

- Three Features approach: This is traditional technique that applies inter weaves' information (HR, SDNN, RMSSD) for emotion recognition.
- Eleven Features approach: Our proposed technique that applies both inter-beat and within-beat information (HR, SDNN, RMSSD, QT, STDEV(QT), PR, STDEV(PR), STDEV(QRS), ST, STDEV(ST)).

The Post Hoc Test's results are showed in figures 3 and 4. In each pair of emotions, we selected the highest value of confidence interval among three features approach in figure 3 and eleven features approach in figure 4. As shown in figure 3 and 4, the eleven feature approach had more confidence-level than the traditional method and also the classification accuracy is higher as shown in table 2.

Table 2. The comparison of emotion recognition's accuracy between Three Feature and Eleven Feature approaches

Emotion	*Three Features Approach*	*Eleven Features Approach*
Anger	68.57 %	60.00 %
Fear	61.25 %	32.50 %
Disgust	57.14 %	25.71 %
Sadness	64.38 %	45.21 %
Neutral	60.53 %	31.58 %
Joy	56.79 %	28.40 %
Total	**61.44 %**	**37.23 %**

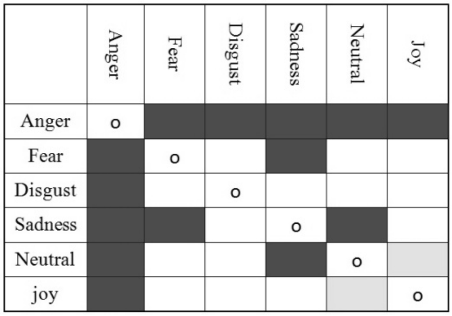

Fig. 3. Three Features Approach Post Hoc Tests in ANOVA

5 Conclusion and Future Work

This system, we focus on emotion recognition in the living space. The RF-ECG sensor is a wearable sensor that uses a wireless connection to the server so the system can monitor the user all the time. Therefore the user is able to move around freely in the living space. We apply a diagnosis method that uses of both inter-beat and within-beat of ECG signals for the emotion recognition with improved accuracy. We reduce the amount of raw data by using analyzed value of ECG signals and statistical data in emotion recognition.

In the future work, we plan to combine more biological signals such as Respiration (RESP), and Skin temperature to improve the accuracy of recognition rate. Physiological signals could be used in health care monitoring in tandem with emotion recognition. While this study deals with very new systems and there are some subjects for research which remain unimplemented such as service generation depends on emotions, they may be useful in the creation of new types of processing systems in the near future.

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