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# Emotion Monitoring from Physiological Signals for Service Robots in the Living Space

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**Abstract**: To increase the amount of happiness in our daily life, we must recover ourselves from displeasing emotional states and try to keep to more pleasing emotions. The way for the user to avoid displeasing emotions depends on the category of the emotion, whether it be fear, anger, disgust or sadness. In this study, we focus on emotion recognition for service robots in the living space. 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 by using analyzed value of biological signals for the emotion recognition. Our system design is based on wireless and wearable physiological sensors for mobility and convenience of users' daily lifestyle.

**Keywords:** Intelligent space, Service robot, Emotion recognition.

## 1. INTRODUCTION

In our everyday lives, we are familiar with automatic mechanisms using implicit commands such as automatic doors, automatic water taps, automatic lamps, etc. Probably the most basic example is the automatic door with an active infrared sensor. The mechanism of the receiver perceives a different pattern of infrared rays when a user enters the infrared coverage zone. The sensor will recognize that the user is approaching the door and transmit a detection signal to open the door. After the user leaves the infrared coverage zone, the receiver receives infrared rays in the normal pattern and a driving source is energized to close the door. For the user, direct commands to open or close the door are unnecessary. The door automatically opens when the user approaches and closes when the user leaves the sensing zone. This mechanism provides convenience and enables a more natural interaction between the user and the mechanism than in a direct command system. However, the automatic door is an uncomplicated system. For a complicated robot system using direct commands, users need to learn how to communicate with the system and additional actions are needed to operate a robot. Therefore, many researchers have been seeking ways to extend implicit commands to more complicated tasks. Our research scope is to generate an implicit command system for daily life in the living space. In traditional implicit command systems, researchers typically pay attention only to human activity monitoring. However, emotions also play an important role in person to person communication and interaction. They allow a sender to express himself (feelings, intention and internal states) and a receiver to better understand signals from the sender. In this study, we therefore observe not only human activities [1] but also emotional states during those activities. There are many studies whose purpose is emotion recognition, for instance, evaluation systems (games, advertisements, computer aides tutoring, etc), health care monitoring, and artificial emotion simulation. Nowadays, there are many techniques to solve these problems. Each technique is suitable for its purpose.

We focus on a biological approach that has advantages over others because peoples' emotions vary in different ways according to environment, culture, education and so on. However, peoples' 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. This approach developed from clinical research for health care monitoring, diagnosis evaluation, and treatment of diseases. Recently, a great deal of attention has been paid to this technique in the literature indicating that a biological evaluation system is more accurate than a questionnaire. Many studies reduce the size of the biological sensors for ubiquitous health care monitoring which makes this approach most suitable for adaptation to our system.

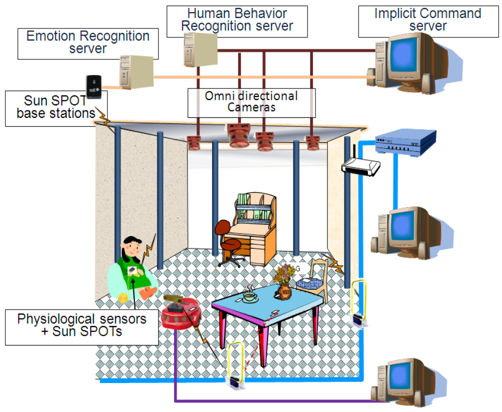


Fig.1 Structured Environment in Intelligent Space.

## 2. METHODOLOGY

### 2.1 System Structured Environment in Intelligent Space

Figure 1 shows the overall system structured environment of this system. In this system we observe the person in the living space which is a wide area. The physiological sensor is selected based on three important criteria. The first criterion is that the physiological signal must be strongly related with the human emotion. The second criterion is the physiological sensor should adhere to human skin without discomfort. The last criterion is the physiological sensor must be wearable and convenient for use in normal daily life. In this study, the Electrocardiogram (ECG) signal is selected. A user wears ECG's electrodes that collect data from the movement of the heart's index. The data will be calculated as a set of instances. Different emotions will come with different physiological data features. This system is designed to be mobile by collecting personal physiological information through wireless connection of RF-ECG sensor as shown in figure 2, while the base station is connected to a PC. This provides the user more freedom to move while the system monitors the person continuously.

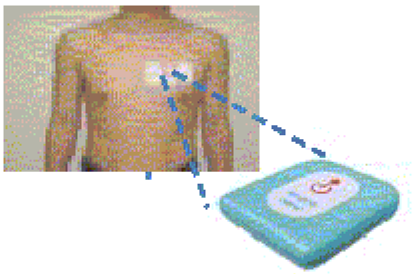

Fig. 2 Wireless Bio Sensor RF-ECG

### 2.2 Feature Extraction

ECG signal is sampled and digitized to be a discrete signal with frequency of 204 Hz. However the amount of data is still very large. To reduce computational time, our features are computed by statistical data from analyzed value of the signal. The continuous wavelet tranforms (CWT) and fast wavelet transforms (FWT) are used for automatic annotation of the ECG cardio cycle. The annotation method consists of two phases: QRS detection followed by P, T wave location. We apply a diagnosis method by using analyzed value of biological signals, so we calculate several parameters that indicate each part of heart's activity.

- **PR-interval**: The portion of the P wave that is produced by atrial depolarization.
- **QRS-interval**: The interval from the beginning of the Q wave to the termination of the S wave, representing the time for ventricular depolarization.
- **ST-interval**: T wave is produced by ventricular depolarization.
- **R-R interval**: The interval from the peak of one QRS complex to the peak of the next as shown on an electrocardiogram. It is used to assess the ventricular rate (1 beat).
- **Heart rate**: The frequency with which the heart beats, calculated by counting the number of QRS complexes or ventricular beats per minute.

$$\text{Heart rate} = 60/\text{R-R interval(s)}$$

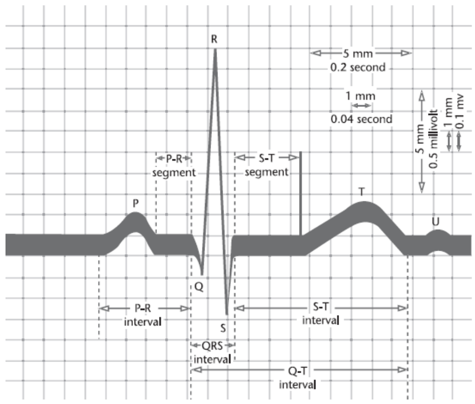


Fig. 5 Normal feature of the Electrocardiogram[5]

The last step is to calculate the statistical data (mean and standard deviation) of PR-interval, QRS-interval, ST-interval, and heart rate. Note: there are two types of standard deviation between heart beats.

- **SDNN**: Standard Deviation of Normal-to-Normal of R-R intervals.
- **RMSSD**: Root Mean Square of Successive Different of R-R intervals.

## 3. EXPERIMENTS

Our experiments are based on International affective picture system (IAPS)[8] and Robert Plutchik's emotional model. The valence level categorizes pleasure/unpleasure emotion into negative, neutral and positive levels. The negative emotional arousal can be categorized into four categories (sadness, anger, disgust, and fear) as shown in figure 3. Biological interpretation was calculated in time-domain. We analyzed whether emotion was caused or not with biological interpretation again.

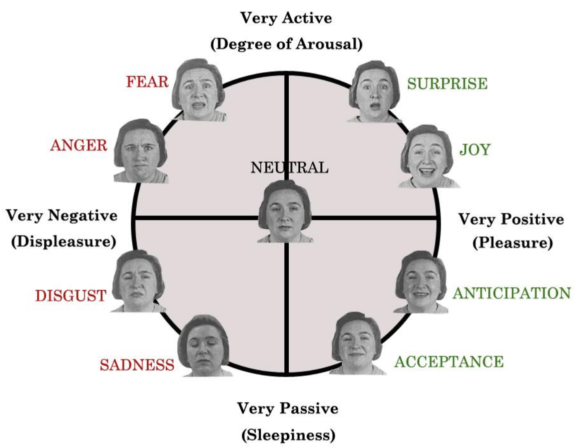


Fig.3 A circumplex for emotions[6].

### 3.1 Experiments on Electrocardiogram (ECG)

We provided the 6 subjects with pre-rated pictures in IAPS which can induce a variety of emotions. In the experiment, we use the same process with IAPS experiments. However we change from pencil-paper based to computer based for questionnaire section to reduce the effort for management of questionnaires. We provide the same questionnaires to the subjects. If subjects do not feel emotions promptly in IAPS, We do not apply the data to an experiment.

In the experiment, we show 60 pictures to the subjects one by one. Each trial begins with a preparation step to train the subjects to familiar and understand the experiment. We attach ECG electrodes on the subject's breast. The, the picture to be rated was presented for 6 s, and immediately after the picture left the screen, the subject made their ratings. A standard 15 s rating period was used, which allowed ample time for subjects to finish the questionnaire. The ECG signal start measure at the same time with the first picture was presented.

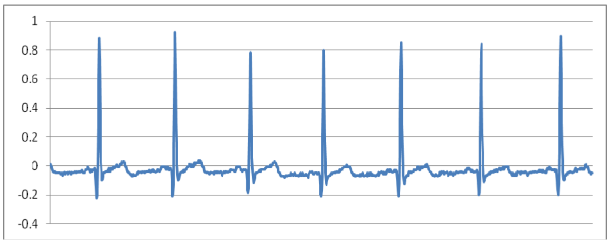


Fig 4. Raw ECG signal measurement/picture

We pre-processing the raw ECG signals with wavelet transform and synthesis to reduce the noise and then we calculate the statistical data of features within and inter waves as shown in Table 1.

Table 1 The statistical data of ECG's features

| Feature | Individual | Mean | SD |
|---|---|---|---|
| Heart rate | ○ | ○ | |
| RR interval | | | SDNN, RMSSD |
| PR interval | | ○ | ○ |
| QRS interval | | ○ | ○ |
| ST interval | | ○ | ○ |

## 4. DISSCUSSION

In our initial studies, we found that the individual heart rate of same emotion have similar pattern as shown in figure 5. Different emotions have different patterns as shown in figure 6. We found some patterns: when a subject experiences "anger", his heart rate will drop first, then suddenly rises up. In the other hand, when a subject experiences "fear", his heart rate is arise for a moment, then drops back to normal.

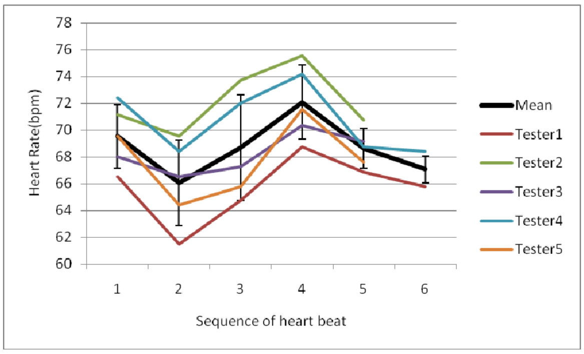


Fig.5 Heart rate of anger emotion

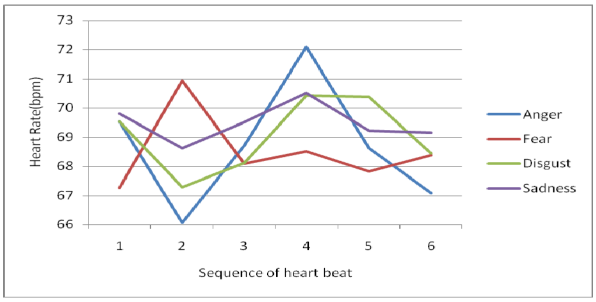


Fig. 6 Mean individual heart rate of each emotion

### 4.1 Data Normalization

Different person have different biological signals. To avoid this effect, each parameter (hear rate, SDNN, RMSSD, QT's mean, QT's SD, PR's mean, PR's SD, QRS's mean, QRS's SD, ST's mean, and ST's SD) was normalized by subtracting the mean of each parameters in the neutral emotion.

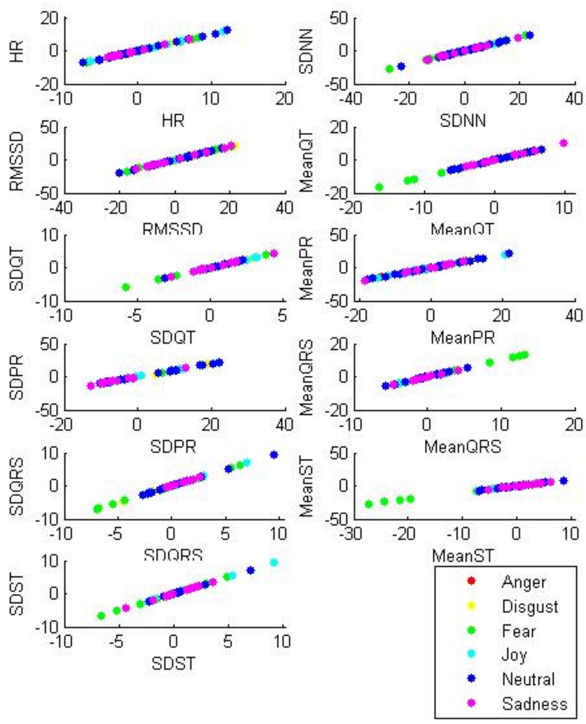


Fig. 6 Normalized data of 11 parameters

**4.2 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 (hear rate, SDNN, RMSSD) for emotion recognition.
- Eleven Features approach: Our technique that applies the statistical data of features within and inter waves for emotion recognition. The features within waves are normally used for disease diagnosis. However, when our emotional state changes, the features within and inter waves also change as shown in table 3.

Table 2. Three Features' Post Hoc Tests in ANOVA

| | Anger | Fear | Disgust | Sadness | Neutral | Joy |
|---|---|---|---|---|---|---|
| Anger | o | | | | | |
| Fear | | o | | | | |
| Disgust | | | o | | | |
| Sadness | | | | o | | |
| Neutral | | | | | o | |
| joy | | | | | | o |

Table 3. Eleven Features' Post Hoc Tests in ANOVA

| | Anger | Fear | Disgust | Sadness | Neutral | Joy |
|---|---|---|---|---|---|---|
| Anger | o | | | | | |
| Fear | | o | | | | |
| Disgust | | | o | | | |
| Sadness | | | | o | | |
| Neutral | | | | | o | |
| joy | | | | | | o |

Note:

95% Confidence Interval

90% Confidence Interval

85% Confidence Interval

**4.3 Linear Discriminate Analysis Classification**

In classification process, we apply LDA to maximize the difference between classes and minimize the variations found in each class. To evaluate the recognition performances, we use 2 sets of 87 data for training and 2 sets of 87 data for testing.

Table 4. Emotion Classification

| Number of features | Accuracy |
|---|---|
| 3 Features (HR, SDNN, RMSSD) | 37.64 % |
| 11 Features | 61.79% |

## 5. CONCLUSION

This system, we focus on emotion recognition in the living space. The ECG sensor is a wearable sensor that uses a wireless connection to the server so the system can monitor the user all the time which allows the user to move about freely in the living space.

We reduce the amount of raw data by sampling an analog signal and converting the digitized data to statistical data in emotion recognition.

We apply a diagnosis method by using analyzed value of biological signals for the 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.

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