EPiC Series in Computing
Volume 81, 2022, Pages 89–100
Proceedings of 11th International Congress on Advanced Applied Informatics

A Method for Estimating Emotions Using HRV for Vital Data and Its Application to Self-mental care management system

Koharu Sano[1], Keiko Ojima[2], Tagiru Nakamura[1], Ryotaro Okada[1] and Takafumi Nakanishi[1*]
[1] Musashino University, Tokyo, Japan
[2] NTT Communications
s1922015@stu.musashino-u.ac.jp, keiko.ojima@ntt.com, tagiru_n@musashino-u.ac.jp, ryotaro.okada@ds.musashino-u.ac.jp, takafumi.nakanishi@ds.musashino-u.ac.jp

Abstract

In this paper, we present an emotion estimation method using heart rate variability parameters of vital data. Recently, as sensors have become more precise and smaller, it has been possible to obtain users' vital data in real-time quickly. In our method, ECG (electrocardiogram) data are measured beforehand while listening to a story with voice narration that evokes emotions and based on the trends obtained through the measurement, the emotions that have a high correlation with the newly acquired ECG data are estimated to be the emotions expressed in the ECG data. With the implementation of our method, it is possible to estimate the user's emotions based on ECG data. In this paper, we also represent the application of our method to chat icons that see users' emotions in real-time. By realizing this application, users will see the changes in their emotions and control their mental health.

1 Introduction

Sensors have become more precise and smaller, allowing users to easily obtain vital data in real-time. Sensors that can measure vital data are becoming smaller and simpler, with the advent of ultra-small biosensors using cardio chips (Neurosky, 2021). For this reason, recent years have seen a lot of interest in telemedicine and telemonitoring using vital data. As an example, a non-contact health management system (Binah.ai, 2021) has been developed to measure vital signs such as SpO2(saturation of percutaneous oxygen), heart rate, respiration rate, and heart rate variability mental stress level using only a smartphone. This is intended for use in telemedicine and telehealth and welfare

* Corresponding author

facilities. Vital data used in these systems are often output in real-time, and the advantage of being able to do this remotely is a good fit for this era and is increasing demand. Real-time vital data is a good way to automatically communicate your information to the outside world.

Therefore, we focused on electrocardiogram (ECG) data that can be acquired in real-time. When we can create a system that estimates emotions from ECG data and displays the estimated emotions as icons on the chat application, we can know our emotions while chatting. When negative emotions are displayed while I am chatting, I can take action to end the conversation early. On the other hand, when you see a positive emotion, you can take action to continue the conversation. As a result, by displaying these emotion icons, it is possible to use them as a guide for controlling one's mental state. In addition, since the displayed emotion icons only show one's own emotions and not the emotions of others, and they are not saved, one can only know one's current emotions. As a result, people can control their own mental health even in situations where they cannot receive mental health care, thus realizing self-mental care management.

In this paper, we present an emotion estimation method using heart rate variability parameters of vital data and its application to real-time chat icon creation corresponding to the user’s emotion estimated by our method. In our method, we measure ECG data while listening to a story with voice narration that evokes emotions, and from the trends obtained by the measurement, we estimate the emotions that are highly correlated with the newly acquired ECG data as the emotions expressed in the ECG data. With the implementation of our method, it is possible to estimate the user's emotions based on ECG data. By displaying the estimated emotions as facial expression icons on the chat application, users can check the changes in their emotions and control their mental health Figure 1 shows an example of representation for users’ emotions by the icons. In other words, by realizing this application, users will be able to check the changes in their emotions and act according to those emotions, thus enabling self-mental care management.

This paper is organized as follows: Section 2 introduces related research. Section 3 describes the research in the field of psychology used to estimate emotions using our method. Section 4 describes the implementation of our method using ECG data. Section 5 constructs an experimental system to implement our method, conducts an evaluation experiment, and presents the results. In Section 6, we conclude this paper.

Figure 1: Example of real-time chat icon creation corresponding to the user’s emotion estimated by our method: The screen on the left is the user's photo, the facial expression icon of the emotion estimated by ECG, and the heart rate. A tap on a user's photo will take you to his or her chat screen (right screen).

2 Related Works

In this section, we show some research related to our method.

Zhao et al. (Zhao & Katabi, Emotion recognition using wireless signals, 2016) have developed a system that uses electromagnetic waves to automatically detect human emotions such as excitement, joy, anger, and sadness. Body sensors, such as ECG monitors, are cumbersome to put on and take off, and there is a risk that the data may become inaccurate due to misalignment as the experiment is repeated. To solve this problem, it irradiates electromagnetic waves onto an individual's body and obtains heartbeat data from the reflected waves. The reflected waves are analyzed by a proprietary machine-learning algorithm to detect the level of excitement and emotion by capturing the slight temporal changes between heartbeats. From this, they infer emotions, and although there are individual differences, they have succeeded in inferring emotions 70% of the time, even for people who are measuring for the first time.

Tivatansakul et al. (Tivatansakul & Ohkura, Emotion recognition using ECG signals with local pattern description methods, 2015) designed a healthcare system focusing on emotional aspects to cope with negative emotions in daily life. In this paper, they focused on emotion recognition using ECG signals, and applied and evaluated local pattern description methods, LBP (local binary pattern), and LTP (local ternary pattern), which are suitable for emotion recognition by facial expressions. The results showed that LBP and LTP can effectively extract ECG features with high accuracy. In the real-time evaluation, they experimentally evaluated the efficiency and effectiveness in recognizing negative emotions. The results show that real-time emotion recognition from ECG signals is sufficiently beneficial and efficient for emotional health care systems to analyze negative emotions and provide support.

Our proposed method calculates heart rate variability parameters from ECG data and estimates emotions based on previously associated emotions, to realize identify changes in one's own emotions, and self-mental care management in response to those changes. Since the connection between ECG data and emotions differs among individuals, we developed a mobile application for emotional elicitation, performed emotional elicitation within the application, and measured ECG data during the elicitation. This application allows us to correlate measured ECG data with evoked emotions.

To elicit emotions, a pseudo-experience is conducted while the user listens to a story with voice narration that elicits emotions. After listening to the voice, the user is asked to select the appropriate emotion, and the ECG data can be related to the emotion. By using this relation, the proposed system estimates and visualizes emotions from the ECG data in real-time. The system visualizes emotions as facial expression icons in real-time on a chat application. In addition, we categorized the emotions obtained during emotion elicitation into four categories and estimated the total of five emotions including four emotions and the normal state.

3 Emotion Classification for Emotion Estimation

In our method, ECG data is used to estimate emotions. The purpose of our method is to estimate and visualize emotions from new ECG data by correlating emotions previously elicited using an emotion-eliciting application with ECG data measured during that time. In this method, the emotions elicited by the stimulus, a simulated experience using voice narration, are classified into four quadrants. Roseman's Primary appraisal dimensions and their consequences (Fredrickson, Atkinson & Hilgard's Introduction to Psychology 15/E, 2009) is used for the four emotional quadrants.

	Occur	Not Occur
Desirable	Joy	Sorrow
Undesirable	Distress	Relief

Table 1: Primary appraisal dimensions and their consequences

Roseman categorized emotions into four quadrants as primary appraisal dimensions and their consequences, as shown in Table 1.

As for Roseman's “Primary appraisal dimensions and their consequences”, since the emotions that fit into those four quadrants are only examples, in our method, a questionnaire is conducted in the implemented application to determine which of the four quadrants is applicable. An example displays of the application implemented for emotion elicitation and questionnaire is shown in Figure 2. This allows us to classify the evoked emotions into four quadrants and we view the selected emotions as the evoked emotions.

4 Emotions Estimation Method for Vital Data and Its Application to Real-Time Chat Icons

4.1 Outline of the Proposed Method

In this section, we show an overview of our proposed method. The outline of our proposed method is shown in Figure 3. The system calculates the values of SDNN, RMSSD, and CVSD, which are indices of heart rate variability parameters, from the ECG data obtained from the ECG measurement device. In this paper, we use wearable electrodes attached to the user, estimate the emotions correlated with these values, and then display an icon that matches the emotions on the chat application.

In this paper, hitoe® from NTT Corporation/Toray Industries, Inc. was used as a wearable electrode. hitoe® is a composite material of the conductive polymer PEDOT: PSS and nanofibers and was developed as a woven bioelectrode for the purpose of acquiring vital data such as heart rate and electrocardiogram measurements (Kawai, et al., Development of functional textile “Hitoe”: Wearable electrodes for monitoring human vital signals, 2017). Since biometric data can be obtained without any burden for a long time just by wearing hitoe equipped wear, it is being used as a vital monitoring tool in many fields.

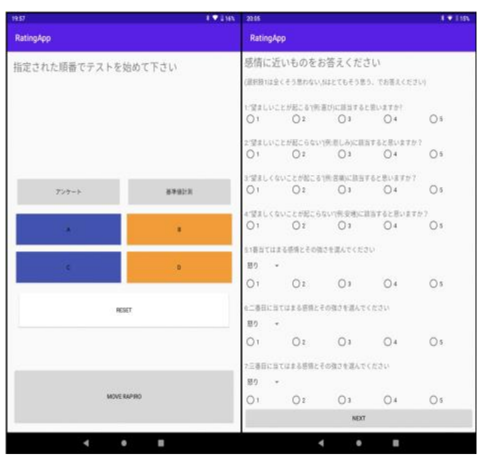


Figure 2: Application Screen: The screen on the left is the home screen of the application for emotion elicitation and questionnaire. From left to right, questionnaire of the situation, baseline measurement, negative emotion elicitation (first part), positive emotion elicitation (first part), negative emotion elicitation (second part), positive emotion elicitation (second part). The screen on the right shows a questionnaire about current emotions, based on Section 3.

In our method, to relate ECG data with emotions, we developed an application that performs voice narration to elicit emotions and a questionnaire to define emotions. Using the application, the ECG was acquired during the emotional elicitation by a voice narration, and the heart rate variability parameters SDNN, RMSSD, and CVSD are calculated from the ECG values. By relating the emotion recalled during emotion elicitation and the ECG heart rate variability parameters measured during the emotion elicitation, it is assumed that when an emotion is elicited, it approximates the value of the linked heart rate variability parameters.

In our method, the ECG is measured in a resting sitting position with eyes closed during wakefulness, and the heart rate variability parameters are calculated. In this method, the ECG is measured in the resting position with the eyes closed for 15 seconds before the voice is elicited, and this is regarded as the normal state. The ECG is measured for 15 seconds in the closed-eyed state before emotional elicitation, which is regarded as the normal state. When listening to the voice narration, the eyes are closed and a questionnaire about the current emotion is given immediately after listening to the voice narration. By repeating these procedures, we can relate the ECG and emotions during emotion elicitation and estimate the emotions. In our method, to classify emotions, we use Roseman's "Dimensions and Consequences of Appraisal" (Fredrickson, Atkinson & Hilgard's Introduction to Psychology 15/E, 2009), introduced in Chapter 3. We categorize users' emotions into four quadrants as defined in Roseman's work: "Desirable/Occur", "Desirable/Not occur", "Undesirable/Occur", and "Undesirable/Not Occur". Users express their current emotions by scoring to these four emotional quadrants in the in-app questionnaire.

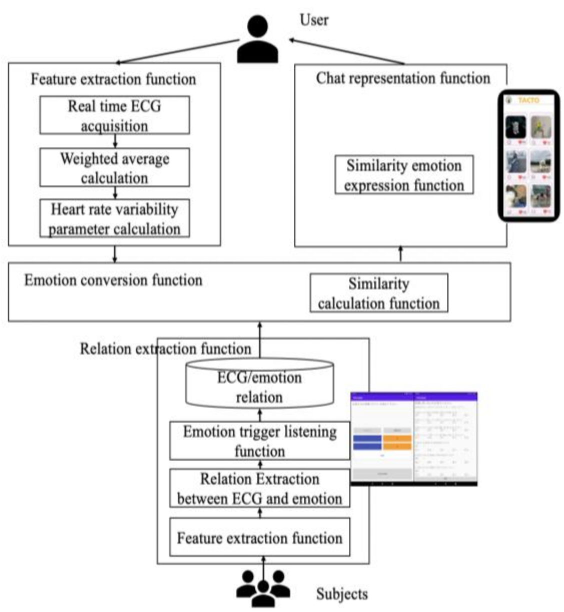


Figure 3: Overview of our proposed method

4.2 Feature Extraction Function

In this section, we show the feature extraction function for ECG data acquired from ECG measurement devices. This system consists of three functions: Real-time ECG acquisition, Noise Reduction, and Heart rate variability parameter calculation.

(1) Real-time ECG Acquisition

To express emotions from a Real-Time ECG, it is necessary to acquire a Real-Time ECG. In this method, vital data are measured using a heart rate measuring device called hitoe® from NTT Corporation/Toray Industries, Inc. To perform real-time emotional icon expression, it is necessary to answer a questionnaire that expresses current emotions, and it is also necessary to perform analysis and calculation of ECG in real-time, so experiments through applications are necessary.

(2) Noise Reduction

Normally, noise may occur when measuring ECG. In the conventional method, noise is removed by statistically analyzing the ECG data of the participants. However, in this method, data is accumulated as "real-time data" or "individual-specific data," making it difficult to obtain statistics for multiple participants. Therefore, in our method, as a noise removal method, we remove as noise those RRIs that are less than, or equal to, 300 or more than 2000. By using that value, noise removal can be done in real time.

(3) Heart Rate Variability Parameter Calculation

Among the heart rate variability parameters, three parameters are used in this study. The first is SDNN, which is the standard deviation of RRI (R-R Interval); the second is RMSSD, which is the square root of the mean of the squares of the differences between successively adjacent RRI and is an index of vagal tone strength. A decrease in RMSSD is a decrease in parasympathetic nerve activity. The third is the CVSD, which is the RMSSD divided by the mean of the NNI, and the CVSD is the coefficient of variation of the continuous difference. These values were assumed to be related to emotions, and calculations were made.

4.3 Relation Extraction Function

In this section, we describe a method for associating emotion with ECG, which is used for emotional expression. This function consists of four functions: feature extraction function, relation extraction between ECG and emotion, emotion trigger listening function, and ECG/emotion relation.

(1) Feature Extraction Function

Real-time ECG acquisition, Noise Reduction, and Heart rate variability parameter calculation are performed according to the method described in Section 4.2).

(2) Relation Extraction between ECG and Emotion

In our method, the relationship between ECG and emotion is made by measuring ECG during the elicitation of emotion. Accordingly, it is necessary to obtain an ECG under normal conditions. Therefore, by acquiring the ECG at rest for 15 seconds, the ECG at a normal state is acquired. Note that the reference value is measured at the very beginning of the experiment to avoid triggering emotions.

(3) Emotion Trigger Listening Function

In our method, the objective is to elicit emotions by having the user listen to an audio narration story that evokes emotions. Inducing basic emotions to collect data in an experiment generally involves five methods: audiovisual, imagery, music, memory recall, and situational judgment (Siedlecka & Denson, Experimental methods for inducing basic emotions: A qualitative review, 2019). Less common methods include spontaneous conversation and discussion (Park, et al., K-EmoCon, a multimodal sensor dataset for continuous emotion recognition in naturalistic conversations, 2020), driving (Healey & Picard, Detecting stress during real-world driving tasks using physiological sensors, 2005), video games (Yang, et al., Physiological-based emotion detection and recognition in a video game context, 2018), and virtual reality(Shahid, et al., Emotion

Recognition System featuring a fusion of Electrocardiogram and Photoplethysmogram Features, 2020). Listening to music is another popular way to activate emotions through lyrics, melodies, and tempo changes (Krumhansl, Music: A link between cognition and emotion, 2002). However, to induce strong emotions, we tried to induce emotions by having participants listen to a story. This is because we thought that by focusing on auditory perception, we could induce emotion through memory recall and simulate the story. The story used in this project consists of two parts: a negative story that triggers negative emotions and a positive story that triggers positive emotions. For the elicitation of positive emotions, we use the CD that comes with "Introduction to Meditation with Yoga" (in Japanese) (Watamoto, Introduction to Meditation with Yoga, 2006), which is said to allow you to experience a sense of freedom and peace, free from the constraints of everyday life. This story contains the narration of the meditation guide by the author of this book, and it is an easy way to meditate by following the voice of the author, adjusting your posture, and imagining the inside of your body. The story is divided into two main chapters: "Learning to Breathe Slowly" and "Deepening Meditation by Adjusting the Seven Chakras of the Body One by One.

Cakra is said to be a pathway of chi along the spine in the center of the human body, and the seven points on the line are called Chakra, which is said to affect both the mind and the body. The two chapters in this book are combined into one.

To elicit negative emotions, we adopted "Death Experience Lesson" (in Japanese) (Yamazaki, *Death Experience Lesson, 2015*), which is said to provide a simulated experience of one's own death. For the death experience lesson used for negative emotion elicitation, a third party read the story and recorded the voice of the third party, which was used as one of the contents for emotion elicitation. This story was used in a workshop for young students to deepen their understanding of death by simulating the process of dying, and to confirm that life shines only because of death. The story consists of 10 chapters: "stomach distress," "to be retested," "cannot sleep due to anxiety," "family is called," "cancer is announced," "school is suspended," "treatment is stopped," "pain increases," "consciousness becomes fuzzy," and "last breath," which are used throughout the story. In the Death Experience Lesson for eliciting negative emotions, a third party reads the story, and the voice of the third party is recorded as one of the contents for eliciting emotions. Also, in the death experience lesson, the students wrote down the things that were important to them to experience loss and then erased them one by one during the story.

These two stories were divided into six chapters each, with the first half being chapters 1-3 and the second half being chapters 4-6. These were divided into four sets: the first half of the positive story, the second half of the positive story, the first half of the negative story, and the second half of the negative story.

In addition, the "Death Experience Lesson" consists of writing down important things to experience loss, and then erasing them one by one during the story. These two stories are each divided into six chapters, three in the first half and three in the second half, making four sets. (Table 2).

Story Categories	Emotional Trigger Story
Standard	standard value
A	Negative1-3
B	Positive1-3
C	Negative4-6
D	Positive4-6

Table 2: Relationship between story categories

To prevent the order effect, two patterns are prepared for the participants: "A→B→C→D", which starts with negative emotion elicitation, and "B→A→D→C", which starts with positive emotion elicitation. By changing the order in which emotions are elicited, the goal is to prevent order effects caused by the elicitin questionnaire response function. A questionnaire on current emotions is given at the end of each chapter to define the emotions that are being elicited. The content of the questionnaire is selected from the four emotional quadrants listed in the emotional classification in Section 3. In each of the four emotional quadrants, respondents were asked to rate the degree to which the statement was true on a five-point scale from "very true" to "not true at all". In each of the four emotional quadrants, the participants rated the extent to which the statements were true on a 5-point scale from "very true" to "not true at all". This means that each chapter will have a total of 4 questions to answer. These tasks have been performed a total of 12 times, 6 chapters each for positive and negative emotions.

(4) ECG/Emotion Relation

To relate ECG data with emotions during emotion elicitation, it is necessary to divide the ECG data into scenes. ECG data that has passed through the feature extraction function in Section 4.2) is saved for each scene. We can relate the ECG data with the emotions in each scene.

4.4 Emotion Conversion Function

In this section, we describe a method for converting real-time ECG data into emotions using the emotion-related ECG data obtained in Section 4.3. From now on, we refer to the ECG data associated with the chapter emotions obtained in Section 4.3 as the emotional ECG data.
Real-time ECG acquisition, Noise Reduction, and heart rate variability parameter calculation are performed.

To express emotions in real-time, it is necessary to estimate emotions by comparing the emotional ECG data acquired in Section 4.3) with the real-time ECG. Emotional ECG data stores three values of SDNN, RMSSD, and CVSD per chapter of the story. From here on, ECG data at normal times is included in "Emotional ECG data" as normal ECG data. Therefore, ECG data (SDNN, RMSSD, CVSD) for a total of 13 scenes (6 chapters of positive story, 6 chapters of negative story, and normal time) are stored in the emotional ECG data.

Similarity calculation between real-time ECG and emotional ECG is performed by SDNN, RMSSD, and CVSD respectively. For each of the three indicators, get the three scenes that are judged to be similar in each. The emotion in the scene with the highest number of votes among the three extracted scenes is the emotion closest to the current emotion.

4.5 Chat Representation Function

In this section, we describe a method of expressing the emotion inferred by section 4 as an expression icon in the chat.

To represent the emotion of the scene with the highest number of votes derived in Section 4.4) as the current emotion, our method employs the representation of a facial expression icon on the chat application. Preliminary experiments showed that the emotions elicited in chapters 1-3 and 4-6 were like each other. This tendency was true for both positive and negative emotions. Therefore, the emotion of the scene with the highest number of votes is regarded as the current emotion, and the expression icon corresponding to that emotion is displayed on the chat application. By displaying in the chat application, the facial expression icons corresponding to the emotions elicited in story categories A, B, C, and D, users can see their emotions as facial expression icons in real-time. Expression icons can instantly predict approximate emotions so that you can immediately notice your own emotions. In this way, you can objectively perceive the changes in your emotions and take action to control them.

5 Experiment

First, we conducted an experiment using the system presented in Section 4. In this section, we describe the results of the system evaluation. Section 5.1 describes the experimental environment. Section 5.2) describes the system evaluation result.

5.1 Experimental Environment

This experiment was conducted on 5 healthy men and women in their 20s. The measurements were taken while they were sitting in a comfortable position with their eyes open. During the normal measurement and emotional elicitation, the application system prompts the user to close his or her eyes, and the ECG data was retrieved with eyes closed. The experiments were undertaken in compliance with national legislation and the Code of Ethical Principles for Medical Research Involving Human Subjects of the World Medical Association (Declaration of Helsinki).

5.2 Experiment 1: Investigations of the emotions elicited by listening to the stories.

In experiment 1, we investigate the emotions elicited by listening to the stories defined in section 3.4. The details of the method are described in Section 3.4. Subjects listen to six positive stories and six negative stories. Immediately after listening to each story, subjects express their current emotions by scoring to four emotional quadrants defined by Roseman. Subjects score each story on five-point ratings from 1 to 5.

Figure 4 shows the results of the questionnaire. We took a questionnaire using the method described in section 4.3.3) then calculated the sum of the five people's five-point ratings to show the percentage of emotions in the four quadrants of each scene. Figure 4 shows the proportion of emotions in the four quadrants of each scene, categorized into the "story categories" in Table 2. As a result, In the Positive1-3 group, “Undesirable/Not Occur” was the most frequent response and listening to the Positive1-3 group elicited the emotion “Undesirable/Not Occur”. In the Positive4-6 group, “Desirable/Occur” was the most frequent response and listening to the Positive4-6 group elicited the emotion “Desirable/Occur”. In the Negative1-3 group, “Desirable/Not occur” was the most frequent response and listening to the Negative1-3 group elicited the emotion “Desirable/Not occur”. In the Negative 4-6 group, “Undesirable/Occur” was the most frequent response and listening to the Negative 4-6 group elicited the emotion “Undesirable/Occur”.

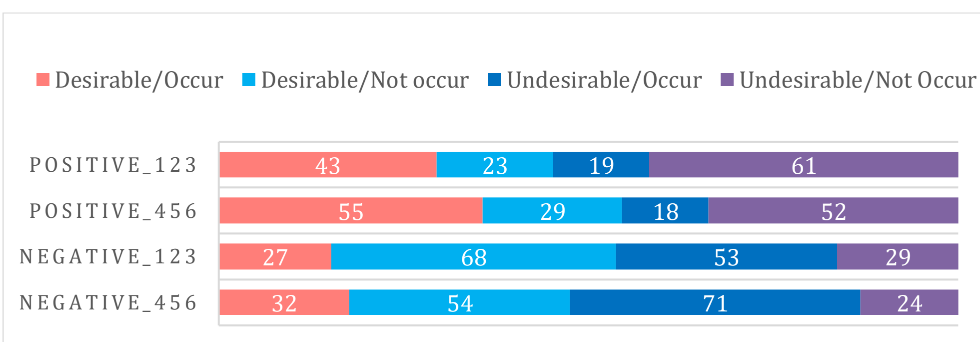


Figure 4: Relationships between the four quadrants of emotions and the story

5.3 Experiment 2: Extraction of Features from The ECG Data When Subjects Listen to Each Story.

In Experiment 2, we obtain the SDNN, RMSSD, and CVSD when listening to the story defined in Section 3.4. The details of the method are described in section 4.2.3.

Subjects listen to six positive stories and six negative stories. While listening to each story, we obtain ECG data and calculate SDNN, RMSSD, and CVSD from it.

Figure 6 shows the results of SDNN, RMSSD, and CVSD for each subject, obtained when listening to the stories defined in section 4.3. In these figures, green points show standard state, blue points show the negative stories (chapter 1 to 6) and red points show positive stories(chapter 1 to 6). Since the purpose of this study is not to obtain statistical ECG data, but to consider individual differences and to estimate emotions specific to everyone, the results of two of the five experimenters are represented and explained.

The results for participant 1 are shown below. In SDNN, the positive stories are relatively higher than the negative stories. RMSSD and CVSD gave similar results. In general, a decrease in RMSSD is a decrease in parasympathetic nerve activity. In Positive4-6, the parasympathetic nervous system was significantly activated, and in Positive1-3, the values increased significantly. After the experiment, experimenter 1 stated that he was puzzled at first because he had no experience with meditation, which was used to elicit positive emotions. Therefore, it is speculated that the confusion appeared at the beginning of the experiment, and as the participants became accustomed to Positive 4-6, they began to feel a sense of relief. as for the changes in Negative 4-6, it is considered that the story of Negative 5 may have moved their emotions significantly because of the scene just before death.

The results for participant 2 are shown below. SDNN, RMSSD, and CVSD gave similar results. The values of Positive 1-6 and Negative 1-3 were relatively low, suggesting that the parasympathetic nervous system was dominant. In negative 4-6, the values are significantly higher. Therefore, it is considered that the emotions were greatly affected by Negative 4-6.

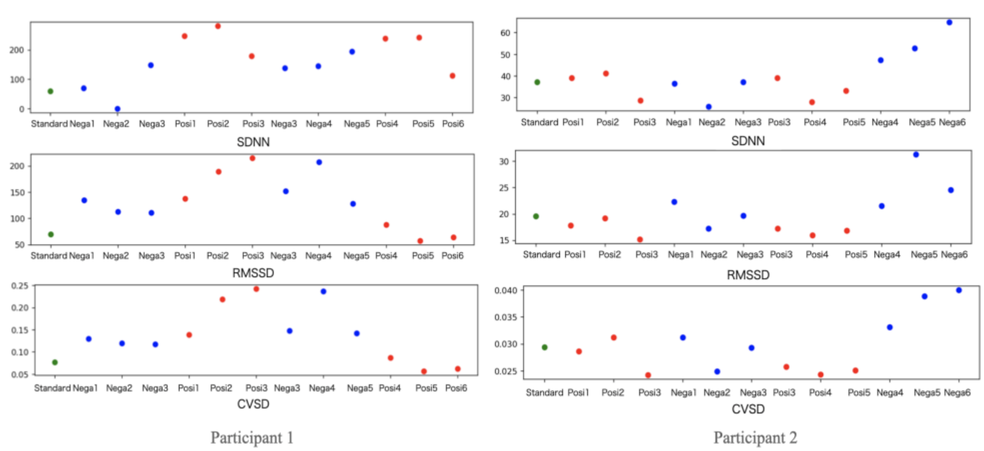


Figure 5: Experimental results for participant

5.4 Experiment 3: Application to Representation of Facial Expression Icons.

In Experiment 3, we investigated the validity of this system. The way it works is that the subject experiences the system and after the emotion is associated with the (SDNN, RMSSD, CVSD) values. They listen to the emotion-evoking narration again and verify if the icons related to the story they are listening to are displayed. The details of how to represent them as facial expression icons on the chat are described in Section 4.5. Icons associated with narratives that evoke emotions were defined by the author based on the results of Figures 4 and 5. (Table 3: Defined Icon). For environmental reasons, this experiment will be conducted on the author only.

Table 3 shows the relationship between icons and stories and the results. Defined Icon shows the icons related to the story, as defined by the author. Result Icon shows the results of the icons displayed after listening to the story. This shows the validity of this system. Of the five icons, three stories, Positive Stories B and D and Standard were able to display the relevant icons. However, for negative stories A and C, the icons for B and Standard were displayed, and for negative stories, the associated icons were not displayed. As a result, the negative story was listened to for the second time, and we speculate that the participants became accustomed to the story and felt relieved that it was proceeding as expected because they knew how it would unfold. Therefore, the results were as expected for the positive story and normal state, but not for the negative story.

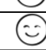
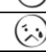
Story Categories	Emotional Trigger Story	Defined Icon	Result Icon
Standard	standard value		
A	Negative1-3		 
B	Positive1-3		
C	Negative4-6		 
D	Positive4-6		

Table 3: Relationship between story categories and icons displayed

6 Conclusion

In this paper, we presented an emotion estimation method using heart rate variability parameters of vital data, and its application to the display of icons corresponding to one's emotions in a chat room by using estimation method. In our method, ECG data are measured beforehand while listening to a story with voice narration that evokes emotions and based on the trends obtained through the measurement, the emotions that have a high correlation with the newly acquired ECG data are estimated to be the emotions expressed in the ECG data. With the implementation of our method, it is possible to estimate the user's emotions based on ECG data.

We also represent an application to chat icons that can express the user's emotions in real-time. By realizing this application, users will be able to check the changes in their emotions and act according to those emotions, thus enabling self-mental care management.

Our future works include the realization of emotion estimation using ECG data with additional emotional elements, improvement of the accuracy of emotion estimation using machine learning, and the combination of vital data other than ECG data. Further improvement of accuracy can be expected by developing these methods.

Acknowledgments

I would like to thank Mr. Akitoshi Hashizume for his advice and guidance in the development of the emotion-inducing application. I would also like to thank Mr. Sho Yamaguchi for his voice narration of the negative emotion elicitation. I would also like to thank the members of Musashino University's TransMedia Tech Lab for their cooperation in the experiment.

References

Binah.ai. (2021). *The New Way to Extract Health Data Is Software-based*. Retrieved from https://www.binah.ai.

Fredrickson, B. N.-H. (2009). *Atkinson & Hilgard's Introduction to Psychology 15/E.*

Healey, J. A., & Picard, R. W. (2005). *Detecting stress during real-world driving tasks using physiological sensors*. IEEE Transactions on intelligent transportation systems, 6(2), 156-166.

Kawai, N., Ogasawara, T., Nakashima, H., & Tsukada, S. (2017). *Development of functional textile "Hitoe": Wearable electrodes for monitoring human vital signals.* IEICE Commun. Soc, 11, 17-23.

Krumhansl, C. L. (2002). Music: *A link between cognition and emotion.* Current directions in psychological science, 11(2), 45-50.

Neurosky. (2021). *ECG biosensor: Enabling true differentiation for OEMs, ODMs, and service providers.* Retrieved from http://neurosky.com/biosensors/ecg-sensor.

Park, C. Y., Cha, N., Kang, S., Kim, A., Khandoker, A. H., Hadjileontiadis, L., ... & Lee, U. (2020). *K-EmoCon, a multimodal sensor dataset for continuous emotion recognition in naturalistic conversations.* Scientific Data, 7(1), 1-16.

Shahid, H., Butt, A., Aziz, S., Khan, M. U., & Naqvi, S. Z. H. (2020, December). *Emotion Recognition System featuring a fusion of Electrocardiogram and Photoplethysmogram Features.* In 2020 14th International Conference on Open Source Systems and Technologies (ICOSST) (pp. 1-6). IEEE.

Siedlecka, E., & Denson, T. F. (2019). *Experimental methods for inducing basic emotions: A qualitative review*. Emotion Review, 11(1), 87-97.

Tivatansakul, S., & Ohkura, M. (2015). *Emotion recognition using ECG signals with local pattern description methods.* International Journal of Affective Engineering, IJAE-D.

Watamoto, A. (2006). *Introduction to Meditation with Yoga.* (in Japanese) Shinsei-Syuppannsya.

Yamazaki, A. (2015). *Death Experience Lesson.*(in Japanese) Sanma-ku Syuppann.

Yang, W., Rifqi, M., Marsala, C., & Pinna, A. (2018, July). *Physiological-based emotion detection and recognition in a video game context.* In 2018 International Joint Conference on Neural Networks (IJCNN) (pp. 1-8). IEEE.

Zhao, M., Adib, F., & Katabi, D. (2016, October). *Emotion recognition using wireless signals.* In Proceedings of the 22nd Annual International Conference on Mobile Computing and Networking (pp. 95-108).