SHIBAURA INSTITUTE OF TECHNOLOGY

DOCTORAL THESIS

The Evaluation and Application of Bio-Emotion Estimation Methods

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SHIBAURA INSTITUTE OF TECHNOLOGY

Abstract

Graduate School of Shibaura Institute of Technology
Doctor of Philosophy
by Chen FENG

People have been putting a tremendous amount of time into electronic devices in daily life due to the COVID-19 pandemic. Consequently, social media has been increasingly used. As more and more people turn to it, some problems are caused by its growing clout, among which negative content, especially misinformation, is the major influence. However, exposure to the negative content may also result in users' negative emotions. Furthermore, they tend to spread or reply with negative content in a negative mood. To avoid this, we propose detecting the users' emotion stats and informing them of the results to help them regulate emotions while they use social media.

First, an appropriate emotion estimation method is required to detect users' negative emotions. The increasingly important emotion estimation based on different features has been studied in the affective computing field in recent years. Among previous studies, Ikeda's bio-emotion estimation method integrates physiological signals related to emotion with the psychological model, which allows people to estimate emotion objectively with simplified sensors. Such benefits make this method available for daily usage. However, the evaluation of this method is not enough. To apply this method to our proposal above, evaluating Ikeda's bio-emotion estimation method is the first step of the research. We conduct aromas to evoke specific emotions to evaluate this method since the aroma is wildly applied to therapies. We compared the estimated result with the classic subjective emotion evaluation self-assessment manikin (SAM) result to evaluate the bio-emotion estimation result. Through the experiment, we found that among four of five types of aromas, the bio-emotion estimation result is matched to the SAM result, except for one negative aroma, which caused an increase in heart rate. In this case, the bio-emotion estimation method result is the opposite of the SAM result. This experiment demonstrates the validity of Ikeda's bio-emotion estimation method in daily emotion-evoking situations.

After evaluating the bio-emotion estimation method, we aim at the second proposal to inform users of their emotion state. Since the evaluation of Ikeda's bio-emotion estimation method turned out well, we combined the bio-emotion estimation method with the closed-loop biofeedback method to inform users of the results. To this end, the second study was conducted to evaluate the subjective opinion of users with a questionnaire, which is to figure out whether the feedback of bio-emotion is acceptable for users. We also designed a prototype system to conduct the second experiment based on the proposal. According to the questionnaire and an interview-based survey in this experiment, most respondents who experienced the system have positive attitudes toward it. Therefore, we improved this system and compared the physiological signal changes of the users before and after the feedback.

Under the positive emotion condition, we found a significant difference between the rest and post-feedback procedures on pNN50. However, this result might be caused by the continuity of positive emotions and the short duration of the feedback. The user's negative emotions are deepened when their subjective emotion state is inconsistent with the estimated emotion state, which we believe is due to their different emotional intelligence and traits. In addition, given the fragmented usage scenario of social media, we turned the time-period bio-emotion feedback into real-time emotion feedback. On this basis, the fact that different users hold opposite opinions about bio-emotion feedback is due to the different emotion intelligence of users. Through the real-time bio-emotion feedback system, we noticed two problems. Firstly, the bio-emotion feedback based on the time period does not fit the social media scenario. Secondly, users have varying needs for bio-emotion feedback due to the differences in their trait emotional intelligence questionnaire (TEIQue). To address these problems, we redesigned the system. First up, we translated the time-based bio-emotion feedback into real-time emotional feedback. Next, actual negative content from social media was used as emotion evocation material. Finally, the questionnaire we conducted covers two aspects, the TEIQue and the user experience questionnaire (UEQ). Based on the result of the TEIQue, we classify the participants into different groups. We found a significant difference between the low self-control and high self-control groups. The comparison between these groups revealed that the group with low self-control was more relaxed than the group with high self-control. We also carried out a case analysis on a representative sample. The case analysis result demonstrated that bio-emotion feedback unconsciously changed the users' emotional states in many cases. Based on the result of UEQ, we show the perspicuity of our system.

In conclusion, real-time bio-emotion feedback impacts users' emotional states. The application of bio-emotion feedback in social media can be expected. Meanwhile, in this study, biosensors were applied under laboratory conditions. Therefore, we consider applying a wearable device to provide feedback on specific negative emotion states of users during social media usage. Meantime, since the bio-emotion feedback regulates the user's emotional state unconsciously, we believe it can also significantly contribute to mediating the user's emotional state and improving mental health.

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List of Abbreviations

SDGs	**S**ustainable **D**evelopment **G**oals
BEEM	**B**io-emotion **E**stimation **M**ethod
CNS	**C**entral **N**ervous **S**ystems
ANS	**A**utonomic **N**ervous **S**ystems
EEG	**E**lectro**E**ncephalo**G**ram
HRV	**H**eart **R**ate **V**ariability
EMG	**E**lectro**m**yo**g**raphy
ECG	**E**lectro**c**ardio**g**raphy
EDA	**E**lectro**d**ermal **A**ctivity
BVP	**B**lood **V**olume **P**ulse
SKT	**Sk**in **T**emperature
RESP	**Resp**iration
SAM	**S**elf-**A**ssessment **M**anikin
TEIQue	**T**rait **E**motional **I**ntelligence **Que**stionnaire
UEQ	**U**ser **E**xperience **Q**uestionnaire

Chapter 1

Introduction

1.1 Background

Emotions are essential to human beings, not only reflecting their current physiological and psychological state[1], but also influencing their cognitive decisions and interpersonal communication. As a result of the COVID-19 pandemic, interpersonal communication is no longer limited to offline.[2] Interpersonal communication is increasing online through social media. In these social media-based interpersonal communications, human emotions are more likely to be stirred up due to the specificity of social media.[3] For example, the problems of misinformation and cyber violence in social media are becoming more serious.[4] Usually, misinformation in social media leads users to negative emotions. Studies have shown that when users are under a negative emotion state, they are more likely to respond to negative messages with overly aggressive language or retweet them.[5] This situation expands the negative contents on social media and affects even more users. At the same time, users who receive these negative messages will also fall into negative emotions. The long-term accumulation of negative emotions can even affect mental health[6]. Mental health plays an essential way in human beings. First, the mental health of the population is relay on government policies; second, the individual mental health can use the psychological interventions[7]; and third, as a novel technology, the combination of computer science methods has proposed multiple ways to help the users with maintaining the health[8]. For the first mental health strategy, regarding government policies, the influence and improvement of mental health are mainly reflected in the improvement of laws and working and living conditions[7]. The second strategy is about psychological intervention. Psychological intervention is usually in the case of patients' self-consciousness. Based on the patient's self-report, the psychologist will provide targeted treatment to the patient[7]. Usually, these methods include cognitive-behavioral therapy, person-to-person therapy, etc[9]. In addition to these cognitive therapies, the psychologist also conducts the therapies such as play therapy[10], [11], animal-assisted therapy[12], aromatherapy[13] to improve the patient's state. Thirdly, the computer science approach, which combines computer science and psychology, has led to the creation of a new discipline called affective computing[14].

Affective computing was conceived by Rosalind Picard in 1997. In her original work, Rosalind Picard proposed two main purposes of affective computing, one is to give computers emotion and the other is to allow computers to understand human emotion[14]. Both can make a huge contribution to maintaining mental health. One is to give machines emotion: in the case of virtual agents and robot design, to make human interaction with machines a better experience. Enhance social relationship with computers and maintain a healthy psychological state. Second, to make computers understand human emotions. Making machines understand human emotions. This can be broadly classified according to the source of the signal, which include emotion estimation based on external signals and emotion estimation based on internal signals. However, due to the social nature of people, these external signals are sometime concealed. For example, a smiling person is probably not in a good emotional state. In such cases, relying solely on external information to determine a person's emotions can lead to erroneous conclusions. Therefore, some researchers have used the fact that emotions can cause changes in physiological signals[15]to estimate emotions. These physiological signals are not altered by a person's subjective and can present even subtle changes of emotion. Typically, these signals include electroencephalograph (EEG), respiration (RSP), electromyogram (EMG), heart rate (HR), etc. Since these signals are not influenced by subjective consciousness, the emotions estimated from these signals also provide a truer picture of a person's subtle emotional changes. This true response to subtle emotional changes can play a key role in maintaining mental health. We assume to applied emotion estimation on the social media in order to estimate the emotion state of user. Therefore, user can notice their emotional state when they are under negative emotion state cause by the negative contents online. Based on the proposal, there are previous research related to our proposal, which is emotion estimation, and the biofeedback.

1.2 Previews research

1.2.1 Emotion estimation

As the beginning of emotion estimation, the affective computing is formally introduced in 1997. Rosalind Picard concept "affective computing" in her book Affective Computing. In the book, "Affective Computing" is expressed as "computing those measures and analyzes the external manifestations of human emotions and influences them"[14]. The research process of affective computing can be divided into several steps: first, the acquisition of affective information associated with human emotions through various methods; second, the analysis and identification of affective information through modeling; third, the understanding of the results through reasoning about the results; and finally, the representation of the results in a rational way. As a result of her research, Professor Picard concluded that "if we want computers to be truly intelligent and adaptable to humans, and to be able to communicate with us naturally, they should have the ability to recognize and express emotions, and they should have their own emotions". Affective computing is an interdisciplinary and comprehensive study that involves human psychology, brain science, physiology, behavior, art and writing, and other related sciences. The part of the current research on affective computing mainly focuses on emotion estimation, which include facial expressions[16], [17], speeches[18], gestures[19] and human physiological signal emotion estimation. In this study, we divide emotion estimation into two categories based on the information source which are the external information-based emotion estimation and the internal information-based emotion estimation.

The external information-based emotion estimation methods are basing on the emotion related external changes. Such as facial expression, speeches, gesture and so on. In terms of emotion estimation through facial expression, previous studies have shown that the maximum degree of emotional communication can be obtained through human expressions, and emotion estimation through expressions has achieved fruitful research results. Initially, research on affective computing with facial expressions focused on recognizing basic emotions from expressions. When people experience these basic emotions, the corresponding features will be shown briefly from the expressions, so recognizing these features from the expressions can correspondingly identify the corresponding basic emotions. Ekman and Friensen established the Face Action Coding System (FACS)[20] in the 1970s to recognize the corresponding emotions by objective facial expression features. In general, due to the complexity of human emotions and expressions, further extraction, learning and analysis of human facial expression features are needed[20], [21]. Emotion estimation by speech is based on the fact that speech data contains speech content as well as a variety of expressions that vary with tone, intonation, and volume. The basis of emotion estimation through speech is that speech data contains information about the content of speech and its variation with different emotions, such as tone, intonation, and volume[18]. By analyzing such information, it is possible to accurately the different emotion states can be identified more accurately. Among this information, intonation is an important variable that can steadily reflect the degree of emotional arousal[22]. The speech variables can also accurately identify different emotions, including sadness, anger, and fear. In contrast, the estimation rate of disgusted emotion through speech is the worst, and compared with facial expressions, the estimation rate of disgusted emotion through speech didn't get a better result. Compared with facial expressions, speech-based emotion estimation is less accurate, but speech-based emotion estimation is more suitable for online real-time use. Emotion estimation by speech is low-cost consuming, non-invasive, and real-time. In the other hand, Emotion estimation through human posture is mainly based on the body posture and the force of body movement. The research in this area has also received a lot of attention and has achieved certain results. Compared with facial expressions and speech data, the estimation of gesture and motion strength is still difficult. Specifically, the difficulty lies in the fact that the body is larger and more integral than the face, while the freedom of body movement is greater which makes the features extracted from body posture data more complicated. The complexity of the features extracted from body gesture data. Some emotional studies of body gestures focus on human hands, especially on gestures. The study of body gestures has been published both nationally and internationally. Existing studies often combine body gestures, facial expressions, and speech data to synthesize the existing studies usually combine body gestures, facial expressions, and speech data for a comprehensive analysis. On the other hand, the internal information-based emotion estimation method is relied on the physiological signal changes occur with emotion changes. Emotion estimation through physiological signals is mainly based on various physiological signals generated by the body. physiological signals are more objective, realistic, and free from subjective manipulation than facial expressions, voice data, and body postures. Physiological signals are more objective, realistic, not manipulated by subjective consciousness. Therefore, emotion estimation from physiological signals is an important research direction. This study is about the estimation of human emotions through physiological signals. In the following chapters, this aspect will be described in more detail.

Emotion estimation using biological information has been studied extensively. Generally, the use of biological information enables objective estimation of genuine emotion since humans are unable to control their physiological changes such as brain activity electroencephalogram and heart rate. Alarcao and Fonseca reported a survey on emotion estimation using EEG signals. They described a procedure for detecting unconscious emotions from EEG signals[23]. Ikeda et al[24]. combined the EEG signals and heart rate variability with Russell's circumflex model to estimate unconscious emotion[25]. Also, Hiramatsu et al. made a stage support system based on such method[26]. To decide the stage composition, they proposed that the response of the audience can be understood by estimating their emotions using physiological sensors. They used vector decomposition of the emotion estimate method based on physiological information. However, even there are plant of research had applied bio-emotion estimation method, The evaluation of this method is still not enough.

1.2.2 Biofeedback

The association of applied psycho physiological and biofeedback define the biofeedback as "a process that enables an individual to learn how to change physiological activity for the purposes of improving health and performance." Such process has been applied on not only physiological medical treatment, but also the psychology treatment. With the development of wearable sensors, biofeedback is now applied to stress management and yoga and other relaxation activity.

1.3 Issues and Objective

In section 1.1, we proposed a two-step solution to provide the increasing of negative contents cause by users' negative emotion in social media. The first step is to estimate the user's emotion state, and the second step is to inform the user about their estimated emotion state. For these two steps, we discussed the prior research in section1.2. In this section, we focus on the issues of the existing research and our proposed solution.

1.3.1 Issues

Firstly, for emotion estimation. In order to estimate users' emotion. we discussed about the existing research of emotion estimation. Among these multiple emotion estimation methods. The bio-emotion estimate method proposed by Ikeda et, al. only required for simplifies sensing environment, which makes this method is easy to apply to multiple usage. Also, this method combined physiological signals with a psychological model which allows the method estimate users' emotional states quickly into four quadrants. Such benefit makes this method is also suitable for emotion estimation while using social media. However, even there are various research had applied bio-emotion estimation method to different research area. There is a lack of research had evaluated this method.

On the other hand, to inform users about their own emotional state, we consider applying biofeedback method. Therefore, we had discussed about the biofeedback method in section 1.2. As one of the branches of biofeedback, the emotion feedback had already applied on some psychological therapies, the application for daily usage is still not enough. In the meantime, the effectiveness of emotion regulation based on emotion feedback has not been certified. Also, few studies have considered differences in the effect of emotional feedback due to users' trait emotional intelligence

1.3.2 Objective

First of all, in order to evaluate the bio-emotion estimation method, it is necessary to considering developed the emotion evoking materials. Normally the ocean evoking materials using in experiment including audio stimulation, visual stimulation. there is also international database about such stimulation. However, during the experiment there are still some participants reported that their emotion was not being evoked clearly. Therefore, we consider using stimulate which can evoke specific emotion as the experiment material to evaluate the bio-emotion estimation method. On the other hand, aroma has been proved effective on evoking specific emotions[27]. Therefore, we consider using aroma as the emotion evoking material to evaluate the bio-emotion estimate method. We designed an experiment to evaluate the bio-emotion estimate method with five different aromas. As the result, the self-assignment manikin result shows the effectiveness of bio-emotion estimate method, except the extreme situation. Since most of aroma is at the same quadrant, except stench aroma, DMDS. This confirms the availability of the method in normally situations.

Secondly, our objective is to inform user about their emotion state using social media. Since the bio-emotion estimate method is proved effective on in emotion estimation, we proposed to combine bio-emotion estimate method with emotion feedback to inform user about their emotion state. Given that this is the first time we have applied bio-emotion to emotion feedback, it is difficult to say how well users will accept bio-emotion feedback. Therefore, as the first step of our study, we made a prototype system to have a preliminary experiment and used subjective questionnaire to evaluate the willingness of users for using such method. Based on the questionnaire result, we find out that, after using the bio-emotion feedback system, the user has more preference for getting suggestions before express emotion. The significant difference shows that the users could accept the bio-emotion feedback system. As the second step, we use the same system to conduct the second experiment. in this experiment we are aiming at the effectiveness of bio-emotion feedback. However, there are still questions remind. Normally social media include instant messaging[28] and social networking sites[29]. Instant messaging such as "WhatsApp", "LINE" etc., provide instant communication from two users to a group of users. The importance of this type of service is the fluency of dialog which usually happen in seconds. In the meantime, social networking sites such as "Facebook", "LinkedIn", "Instagram" allow users to share their emotion expressions at any time[29]. However, when applying our bio-emotion feedback method to social media such as instant messaging and social networking sites, the bio-emotion feedback method at this stage requires a period of time to estimate users' emotion state. This causes a problem of the best time period to estimate emotion and a problem of the feedback timing. Also, some of the participants mentioned the negative opinion of our system. Since some of the participants feel judged when their bio-emotion feedback result didn't match their subjective emotion while other didn't. Since each participant has different trait emotion intelligence. It was thoughtless to put different type of participant into same group. As the third step of our study, we improved our system. a mean to the first remain problem we changed the bio-emotion feedback in time period into real-time feedback to fit different situation of social media usage. Also, to avoid the influence by different personality of participants, we took a pre-questionnaire to collect participants' trait emotion intelligence. And after the experiment we did the analyze based on grouped participants by the pre-questionnaires result.

1.4 Structure

This paper is divided into six chapters, of which this is Chapter 1, which provides a brief description of the research background, previous research, issues, research objectives, and the composition of this paper. Address to the objective, chapter 2 discusses the previous research in terms of the definition of emotion, emotion estimation, and emotion feedback. In chapter 3, two preliminary experiments are described in detail. First, the evaluation of bio-emotion estimation method by using aroma. Second the subjective validation of the acceptability of bio-emotion feedback. Based on the results of the preliminary experiments in chapter 3, the study and results of bio-emotion feedback using time periods are presented in detail in chapter 4. To address the issues identified in chapter 4, chapter 5 details the improved real-time bio-emotion feedback method, as well as the experimental design and results. In chapter 6, we discuss the overall experimental results and the use of bio-emotion feedback in social media. The future possibilities of bio-emotion feedback for emotion mediation are also presented and summarized in full.

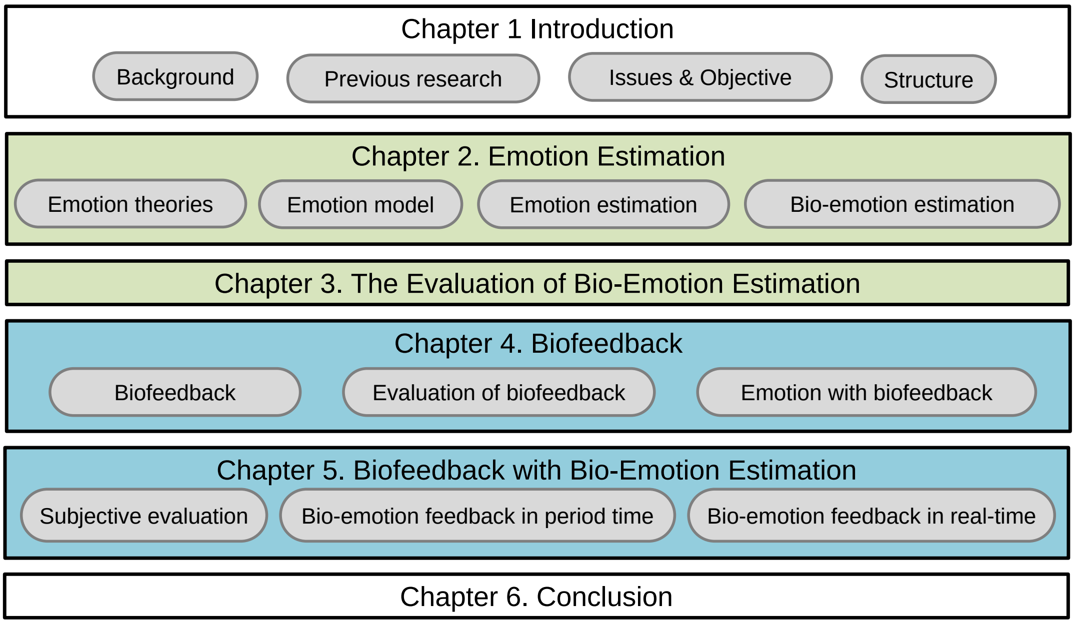

FIGURE 1.1: The structure of this thesis

Chapter 2

Emotion Estimation

As we proposed in chapter 1, The first objective is to estimate user's emotion. To estimate emotion, it is important to clarify the definition of emotion. Therefore, we describe the emotion theory first in this chapter. According to the emotion theory, several psychological emotion model had been proposed by the psychologist. Such psychological emotion models had been applied to estimate emotions. Basing on the information source used to estimate emotion, we divide the previous emotion estimation research into two different types. These two types include the external information-based emotion estimation methods and the internal information-based emotion estimation methods. The external information-based emotion estimation methods are applied the external expression of emotion such as facial expression, speeches, gestures to estimate emotion. On the other hand, the internal-information based emotion estimation methods are applied the emotion changes related physiological change to estimate emotions. Among such emotion estimation methods, Ikeda and colleagues combine multiple internal-information based emotion estimation method with psychological emotion model and proposed the bio-emotion estimation methods. In this chapter, we start with discussing the definitions of emotion and some models of emotion that have been applied to estimate emotions. Next, we introduce different types of emotion estimation methods in the affective computing field.

2.1 Emotion theory

2.1.1 Emotion definition

All human-centered theories start with "people", and emotion theory is no exception. The earliest research on emotion theory was based on the physiological level. The American psychologist William James discussed the definition of emotion in his 1884 book "What Is Emotion?"[30] and gave his insights, and in 1885 the Danish physiologist Carl Lange made similar insights to James. In this theory, emotion is defined as a necessary product of the activity of the vegetative nervous system. This conclusion is also the earliest and famous James-Lange theory doctrine, which, according to the content of the theory, is called by many as the peripheral theory of emotions. Later researchers found omissions in this theory, such as the American physiological psychologist Walter Bradford Cannon[28]. Cannon argued that the James-Lange theory emphasized the importance of the vegetative nervous system and its role in emotion arousal, arguing that emotion production is the result of an organismic change, but ignored the role of other nervous systems and suggested that the center of emotion change is not in the peripheral nervous system. Subsequent studies by Sherrington[31] and Cobos[32] confirmed this challenge raised by Cannon. Thus, Cannon formalized the idea that the thalamus of the central nervous system is the central system that really affects emotion changes. This view was supported and expanded by his student Philip Bard.

In the 1950s, the theory was further refined by psychologist M. B. Arnold. Arnold believed that not only the central design of the thalamus plays a key role in emotion, but also the degree of excitement of the cerebral cortex is a key condition for arousing emotional behavior, and the generation of emotion is the result of the synergistic activity of the cerebral cortex and sub-cortical tissues, and put forward the theory of emotion assessment-excitation? This doctrine states that the process of emotion generation is broken down into three stages: stimulus context, assessment, and emotion generation. This theory also points many researchers to a new research direction, introducing cognitive theory into the study of emotion research theory. In the early 1960s, S. Schachter and J. Singer experimentally proposed a theory of emotion that includes two factors[33], which refer to the physiological arousal of individual emotion and the cognitive arousal of individual emotion, respectively. They pointed out that emotion is actually the result of the combination of the surrounding environmental state and the individual's physiological state, which is manifested through the cerebral cortex, and is simply a cognitive process. Various organs in the human body perceive the environmental factors and transmit the perceptual information to the brain, and the judgment of this information is processed through cognitive factors. This theory became known as the Schachter-Singer theory, and the related model is called the emotional arousal model. Another representative of the cognitive theory of emotion is the American psychologist, Richard Lazarus. Lazarus (Richard Stanley Lazarus)[34]. He proposed that emotions are essentially a perceived response of individuals to things in their surroundings and are the result of the interaction between the person and the environment. Because the interaction between humans and their environment is ongoing and does not stop, humans continuously evaluate, sub-evaluate, and re-evaluate their surroundings on three levels . This series of theoretical studies shows that emotion is a very complex concept, which includes many elements. To define emotions in the most objective and relevant way, it is necessary to combine all these elements in a reasonable way.

Through the systematic organization and in-depth understanding of these theories[35], we have summarized three elements that play a key role in the generation of emotions. The first is environmental change. Without a certain degree of external stimulation, emotions cannot be generated. Even in the famous "sensory deprivation experiment", the experimental environment without external stimulation for a long time is a special source of stimulation.

Second, individual needs. Emotional arousal depends on the individual's needs and the assessment of the expected needs, and the satisfaction of the individual's needs has a key role in influencing emotions and plays a mediating and transforming role between environmental stimuli and emotional responses. The last element is cognition, which is a person's understanding and evaluation of things and the environment. People need to respond cognitively to external stimuli in order to induce different degrees of emotional change in themselves. The analysis of these three elements is an integral part of the study of emotional arousal and change.

2.2 Emotion models

In this section, we discuss about the emotion model used for emotion estimation. Since emotions have a high degree of complexity and abstraction, various theoretical studies have been unable to agree on the estimation of emotions. By reviewing and summarizing the research, we roughly divide the widely used emotion models into two types, one is the discrete model and the other is the multidimensional continuous model. The discrete model is to study each emotion as a mutually separate emotion category. Due to the complexity and abstraction of emotions, numerous theoretical investigations have been unable to agree on how to estimate them. After evaluating and synthesizing the literature, we can generally classify the most extensively used emotion models into two categories: discrete models and multidimensional continuous models. The discrete model is used to examine each emotion as a distinct emotion category.

2.2.1 Discrete models of emotion

The discrete emotion model assumes that human emotions are composed of several discrete emotions and that these discrete emotions are shared across ethnicity and culture and are shared by people. Discrete emotions may be interpreted differently by different cultural backgrounds The discrete emotions may be interpreted differently by different cultures, and the discrete emotions may be mixed to produce complex emotions. Ekman[36], who developed the theory of discrete emotions, believes that discrete emotions must have the following characteristics. First, the basic emotion must come from human instincts; second, all people can produce the same discrete emotion in the same situation; and third, all people express discrete emotions in the same way, and all people express them semantically; fourth, these emotions are expressed in the same way for all people. Fourth, the expression pattern of these emotions must be the same for all people. Based on these four criteria, Ekman obtained the basic emotions include joy, anger, sadness, fear, disgust, and surprise, while common complex emotions include embarrassment, guilt, shyness, and pride. guilt, shyness, and pride. Izard[37] used factor analysis to propose that humans have 11 discrete emotions, which are interest, surprise, pain, disgust, pleasure, anger, pride, and joy. Izard divided the complex emotions into 3 categories. The first category is the synthesis of 2 to 3 types of emotions based on discrete emotions; the second category is the mixture of discrete emotions and bodily sensations; and the third category is the mixture of emotional cognition. Izard classifies compound emotions into three categories, the first being a composite of two to three emotions based on discrete emotions; the second being a mixture of discrete emotions and body sensations; and the third being a mixture of cognitive structures and discrete emotions. Krech, Crutch-field, and Livson et al. divided discrete emotions into four categories[38]: the first category is primitive emotions, which Krech et al. consider happiness, anger, fear, and sadness as the most basic primitive emotions; the second category is emotions related to emotions related to sensory stimuli, such as pain, disgust, and lightness; the third category is emotions related to self-evaluation The third category is emotions related to self-evaluation, including pride and shame, guilt and remorse, success and failure, etc. These emotions determine how an individual's behavior compares and contrasts with objective standards. These emotions determine the comparison and evaluation between personal behavior and objective standards; the fourth category is the emotions related to others, which can be divided into positive and negative emotions. The fourth category is emotions related to others, which can be divided into love and hate in positive and negative terms. Mixing the above four discrete emotions can produce more complex emotions such as sympathy, hate, and hate. The above four discrete emotions can be mixed to produce more complex emotions, such as sympathy, jealousy, regret, etc. Among the above discrete emotion models, Ekman's discrete emotion model is widely accepted by the public.

2.2.2 Multi-dimensional continuous model of emotion

The dimensional space model for emotion estimation is broadly divided into three broad categories: two-dimensional, three-dimensional, and four-dimensional. The representative theory of the two-dimensional model of emotion classification is the circumplex model of emotion classification proposed by Russell[25]. This model was later also mostly referred to as the V/A (Valence-Arousal) emotion model based on its horizontal and vertical axis structure. In the V/A model, the horizontal and vertical axes represent the two measures respectively. The horizontal axis represents the pleasantness, that is, the degree of pleasantness of the user's emotions, with the right and left halves representing positive and negative emotions, respectively, often referred to as the Valence-Arousal of emotions. The vertical axis shows the intensity, which determines whether the emotion is intense or not, and is also called arousal, with high intensity at the top, i.e., high arousal of the emotion, and medium intensity at the bottom, i.e., low arousal of the emotion. The four dimensions of the model constitute the four discrete emotion types, namely, happy, relaxed, bored, and frightened. This model is currently the most recognized and most frequently used emotion model by researchers worldwide[39], [40]. Other two-dimensional classification models also basically follow this dimensional design principle[41], [42].

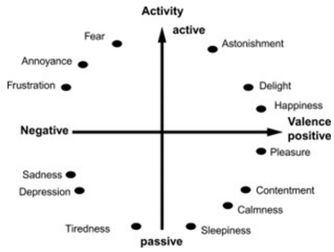

FIGURE 2.1: Two-dimensional classification models

The three-dimensional classification model of emotions was first developed in the late 19th century by the German physiological psychologist Wilhelm Wundt, a German physiological psychologist, proposed in the late 19th century[40]. In this emotion classification model, emotions are classified by the values of three dimensions, each of the axes represent for pleasant-unpleasant; excited-subduing feeling; and feeling of relaxation-feeling of strain. Like the two-dimensional model, the three-dimensional classification model also defines the types of emotions through axes and poles, and all emotions are distributed at different locations between the poles of each axis.

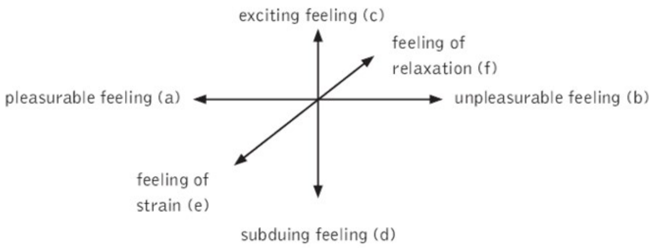

FIGURE 2.2: Three-dimensional emotion classification model

On the basis of the three-dimensional emotion classification model laid down by Vonte, in the 1950s, the American researcher H. Schlosberg, through the study of human facial expressions, proposed a more refined three-dimensional emotion classification model[41], and this more refined classification model was adjusted in the definition of two of the dimensions, except for the retention of the pleasant - unpleasant dimension, the other two dimensions were redefined as controllable to uncontrollable and intensity. In the illustration of this type of emotion classification method, the longer and shorter axes in the image cross-section plane are the pleasant and dominance dimensions, respectively, and a vertical axis indicates the intensity of the emotion. This three-dimensional emotion model consisting of valence-arousal-dominance dimensions has been endorsed by many researchers and is widely used[43], [44]. By the end of the 1960s, Plutchik proposed a three-dimensional emotion classification model with intensity, similarity, and bipolarity as the three dimensions[43]. This type of model is illustrated by an inverted cone and the peripheral planes of this inverted vertebrae are cut, with each cut-out block representing one original emotion, for a total of eight. The distance between two emotions most directly represents the degree of similarity between the two emotions. The vertical axis perpendicular to this inverted vertebra is the intensity of the emotion, with the stronger the upper and the weaker the lower.

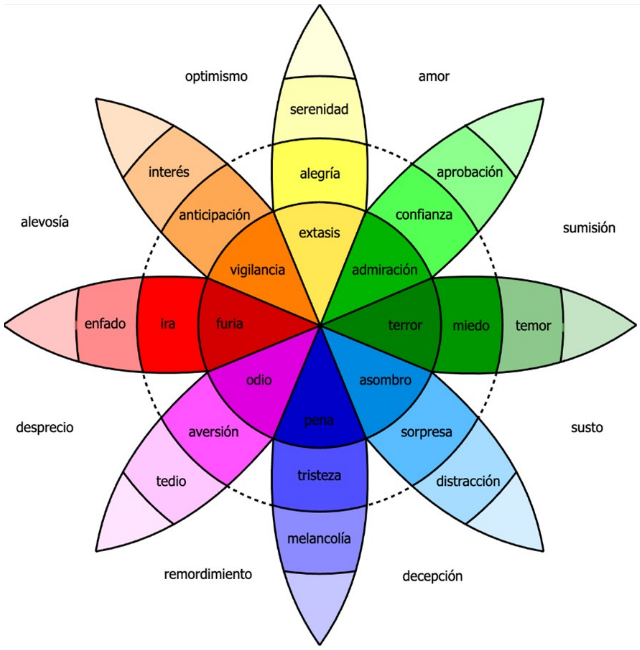

FIGURE 2.3: The Plutchik's model[43]

2.3 Emotion estimation

Emotion estimation has been studied extensively since the end of 1990's. Rosalind Picard conceived affective computing in 1997. In her original work, affective computing, Rosalind Picard proposed two main purposes of affective computing, one is to give computers emotion and the other is to allow computers to understand human emotion. In the last few decades, there has been a surge of interest in the affective computing, especially the "to allow computers to understand human emotion". To let computer to understand human emotion[45], it is necessary to detect the change of human occur with emotion. In this study, based on the different type of information, we divide emotion estimation into two categories. One is the external information-based emotion estimation, and the other is the internal information-based emotion estimation. In this section we will discuss about related research.

2.3.1 External information-based emotion estimation

In recent years, researchers have shown an increased interest in the external information-based emotion estimation. Since this is also the same way human recognize emotion. Ordinary, to understand other's emotion we rely on the external-information they express[46], such as facial expression, speech, gesture and so on. Most of the external information-based emotion estimation also makes computer to "understand" such information. In this section, we describe several representative research on external information-based emotion estimation.

Facial expression

Facial expression-based emotion estimation is aiming to extract the feature related with emotion. There are three major points to be considered when inferring emotions from image recognition. 1. human facial expression database 2. extraction of facial expression features 3. classification of facial expressions.

There are two major types of human expression databases: one is the database based on basic emotions, and the other is based on the subtle changes. For basic emotion based, for example, the JAFFE[16] (Japanese Female facial Expression) contains 213 images of expressions corresponding to the six emotions and neutral expressions from ten Japanese women.

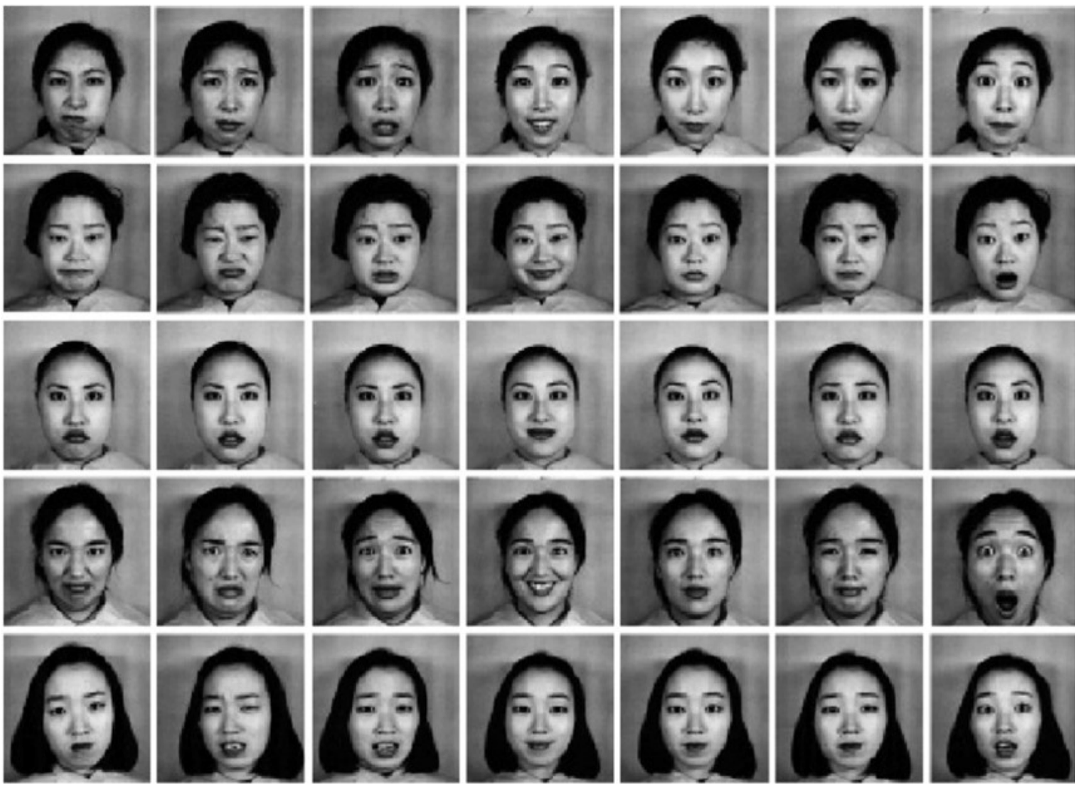

FIGURE 2.4: The example of JAFFE database[16]

On the other hands, database based on subtle changes in facial expressions, with 44 different action units. A database based on the fine transformation of facial expressions, with 44 different action units to display the fine transformation of facial features.For example, the RaFD[17] (Radboud Faces Database) database created by Radboud University (Figure2.5). Each emotion, including "scorn", is recorded from three directions of attention and five angles. While the emotion database becomes richer, there is a limit to the number of facial expressions that can be recorded, which is a problem in emotion estimation research using facial expressions.

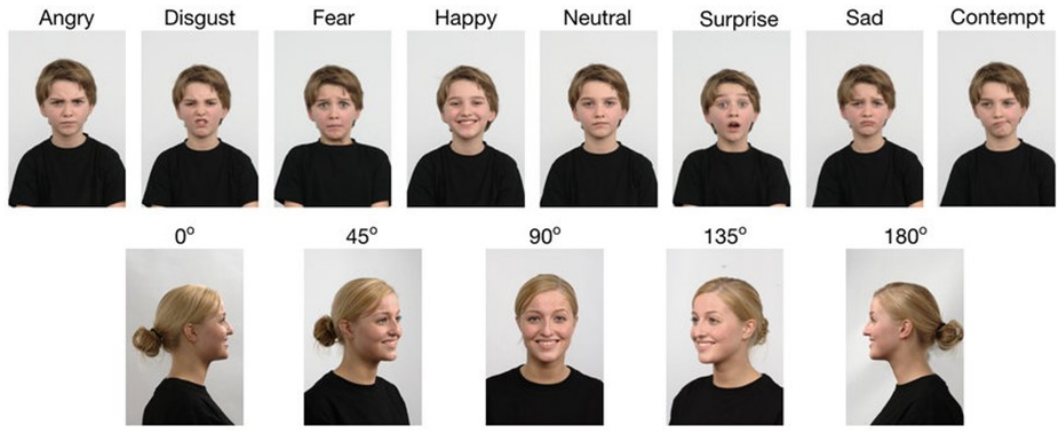

FIGURE 2.5: The example of RaFD database[17]

There are two methods for extracting expression features: from motion features and from deformations. Extraction from kinematic features means extracting the changes in facial features when an expression occurs. In the case of deformation, the change of the surface features is extracted. For deformation, we extract the difference between the face features and the neutral expression when the expression is generated. In recent years, facial expressions have been classified using machine learning methods such as Hidden Markov Model (HMM), Artificial Neural network (ANN), and Support Vector Machines (SVM).

Speech

When human expresses emotion with speeches, the tone changes with emotions. Therefore, emotion estimation based on speech has also been studied. There are some general steps to estimate the emotion. First, an audio database is required. Such databases involve emotion features extracted from the emotion expression audio. Second, emotion corpus is required. In order to build the emotion corpus, it is necessary to collect the speech on the natural degree. There are three types of speech depending on the natural degree. The first is based on natural emotional speech. Natural emotional speech requires recording the speech with emotion expression when the speaker is unaware of recorded (there are legal issues). The second is to use the staged emotional voice. The staged emotional voice are the actors to perform on each emotion. Due to exaggerated expressions, they cannot represent the emotions in daily conversation. The third is to use the induced emotional voice. The induced emotional voice is conducting to using a scenario or video is used to evoke an emotion, and voice is recorded on top of it. However, there are still some problems in inferring emotions from speech. Speech sounds are affected by the content of the speech, the speaker's status, and the speaker's physiological state. In addition, pronunciation habits also differ according to culture and language.

Gesture

Since the emotion estimation on gesture could applied on several different field such as gaming virtual reality, robot human interaction, the emotion estimation based on gesture has been research for several years. The emotion estimation from gesture requires three main point. The1. Body posture database 2. Extraction of body posture features 3. Body posture recognition method. Body posture database contains gestures expressed by each emotion and neutral gestures according to gender. Extraction of body posture features: Mainly head, trunk, hands, and other parts are extracted by tracing the motion when expressing emotion. HMM, dynamic time warping(DTW), decision tree, etc. are currently widely used as body posture recognition methods[47].

2.3.2 Internal Information-based emotion estimation

Physiological signals are very responsive to changes in emotional state, so it is one of the most respected research methods in the field of emotional research. However, since the physiological signals are usually low frequency, unstable, and easily disturbed, it is necessary to use targeted professional instruments and pre-process the obtained signals.

Electroencephalographic signals

The electroencephalographic signal (EEG) can directly reflect the activity of the central nervous system and is also used as the most direct and effective source of physiological information for exploring human emotional states and emotional expression[48]. The EEG signal is a nonlinear, non-stationary signal with strong randomness, which is easily influenced by many other factors, but has a high accuracy of time-domain characteristics and more prominent frequency-domain characteristics than other types of physiological signals, which can help researchers to carry out more targeted research work. According to the segmentation criteria of EEG signals in frequency, the EEG signals are usually divided into five frequency bands [49], which are α wave (this frequency is generally around 8 to 13 Hz, and the most apparent areas of performance are the parietal and occipital regions of the brain, which are also the most basic rhythms of EEG waves. In the absence of external stimulation, a wave is very stable, so the most clear when people are awake, quiet and with eyes closed, while in the person by external stimulation or open eyes will quickly disappear, when the emotional stability of the a wave index will be higher, while the emotional instability of the a wave index will be lower), β wave (frequency generally in 14-30Hz, in the frontal, temporal and central areas of the brain) When a person is tense, excited, hyperactive, or awakened by nightmares, β waves appear in large numbers, indicating

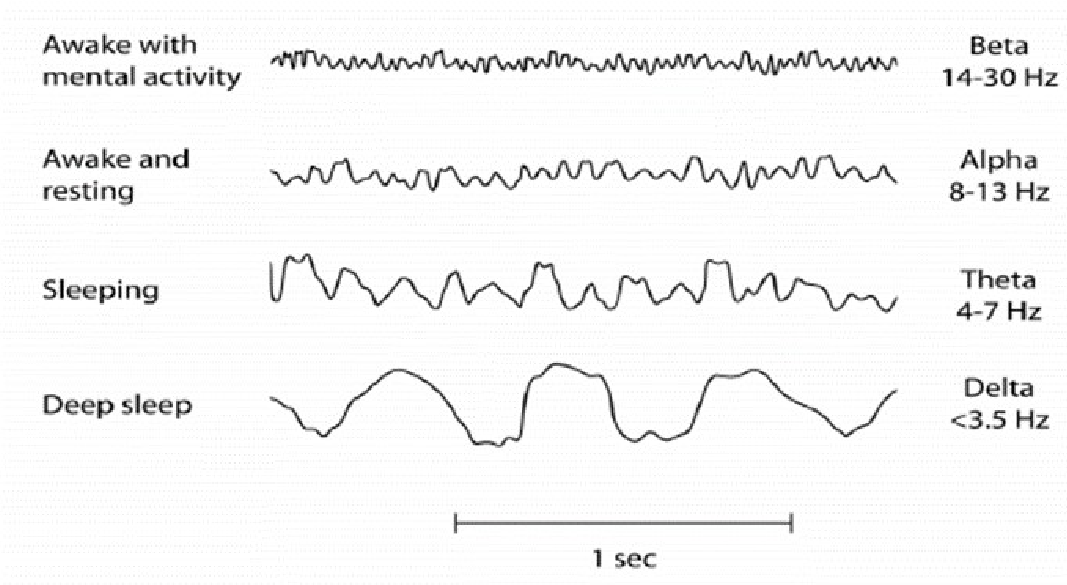

FIGURE 2.6: EEG sample

that the brain is in an excited state), theta waves (frequency is usually 4-7Hz, theta waves are the main EEG component in school-age children between 10-17 years old, but theta waves are also very clear in adults who are frustrated or depressed, or suffering from mental illness), delta waves (generally at a frequency of T3Hz and recorded in the temporal and parietal lobes of the brain, delta waves are usually seen in infants or during periods of mental immaturity, but can also be seen in adults when they are asleep, anesthetized, or extremely fatigued), and gamma waves (generally at a frequency of 31-80Hz, but gamma waves are less frequently seen in human EEG signals, and can be seen when a person is meditating, concentrating on a (gamma waves are less frequent in human EEG signals and appear only when a person is meditating, concentrating on something, relieving stress, or awakening).

The EEG signal is very weak, so it needs to be collected by placing electrodes on the human head, and the electrodes placed are external electrodes for safety reasons. The placement distribution of electrode pads for EEG acquisition, current researchers basically use the international standard 10-20 system[50]. The basic rule of this type of system is to express the relative distance between each point of the scalp electrodes placed on the head, both in 10% and 20%. The rule kind uses two landmark lines, one being the mid-line, positioned at the line from the root of the human nose to the external occipital bulge. The median line has five points from front to back, which are Fpz, Fz, Cz, Pz, and Oz. The front of Fpz and the back of Oz account for 10% of the total length of the median line, and the distance between the remaining points is 20% of the total length of the median line. The other one is the line connecting the two external auditory canals. The markings are the same as the mid-line, and a total of 5 points are recorded from the leftmost point to the middle of the rightmost. 5 points are T3, C3, Cz, C and T4. The outer side of T3 at the leftmost end and the outer side of T4 at the rightmost end each account for 10% of the full field, and the distance between the remaining points

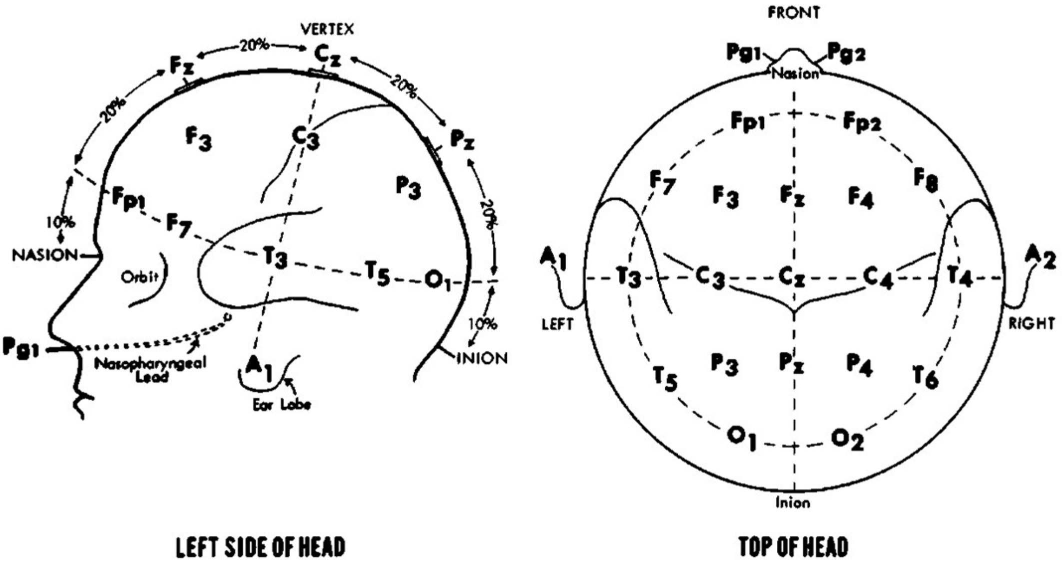

FIGURE 2.7: The Electrode 10-20 system

is 20% of the full length. After four edge points of Fpz, Oz, T3 and T4, a circle is drawn with the center point of the two lines Cz as the center, then two points are taken at equal distances around the circumference between each of the four points, and then one point is taken between each of Fz, C3, Pz and C4 to form a 10-20 system with 21 electrodes, where each electrode point is named regularly, with the numbers indicating the ordering , z indicates 0, Fp indicates frontal anterior lobe, F indicates frontal region, T indicates temporal region, P indicates parietal region, 0 indicates occipital region, and C indicates central region. The electrode distribution of the most common electrode caps such as 16-, 32-, 64-, and 128-conductor are now based on the 10-20 system extension (Figure2.5). In addition to the weak signal, the EEG signal is also susceptible to noise interference from other signals, such as the noise generated by the EEG signal. Generally, in the research, it is filtered by a filter, and then feature extraction is performed after the signal is purified.

Electro-ocular signal

Electro-Oculogram (EOG) is simply understood as the difference in electrical potential between the cornea and the retina, and the signal strength is generally between 0.4 and 10 mV[51]. This potential difference changes continuously with the eye movements driven by the transformation of the human visual field. The potential difference obtained by the electrodes on the left and right sides of the eye is the horizontal eye potential, and the potential difference obtained by the electrodes placed on the upper and lower parts of the eye is the vertical eye potential. It has been shown that when people are surprised, they open their eyes wide or blink continuously, and this eye movement can be recorded by vertical EOG to recognize emotions. However, EOG signals are still predominantly auxiliary in the field of emotion estimation, and no single-mode emotion estimation studies using only EOG signals have yet emerged[51].

Electrical signal of facial muscles

The electrical muscle signal (EMG) is the electrical signal generated along with the contraction of muscle movement, and the electrodes for obtaining the muscle electrical signal are placed at the two ends of the muscle to be studied, and there is a direct relationship between the EMG signal and the contraction of the muscle in the resting situation[52]. Human facial expressions are formed by facial muscle movements and can reflect inner emotions[53]. Earlier studies have found a direct relationship between facial muscle changes and emotional changes, comparing the facial muscle activity of participants in negative emotions (sadness) with that in positive emotions (happiness), showing that the frown muscle region has more muscle activity in negative emotions, while the facial muscle electrical signals in the cheekbone and surrounding muscle regions are more active in positive emotions[54].

Skin-related physiological signals

The skin is the organ of the body that is in closest contact with the external environment and is also very sensitive to changes in human emotions. Galvanic skin response (GSR) and skin temperature (TMP) are the two most important skin-related physiological signals used for emotion estimation.

The human skin itself has a potential difference, and the electrical skin signal is influenced by the sympathetic design of the human body, which changes according to the body's organ systems and emotional fluctuations. The endocrine system also changes when people are stimulated or have emotion swings, which in turn affects the sympathetic nerves, especially on the hands and feet where sweat glands are particularly developed. It has been shown that different degrees of pleasure induce significant changes in the electrical signals of the skin[55].

Skin temperature, understood literally, refers to the temperature of the human epidermis. The human skin is affected by the activity of the sympathetic nervous system, for example, when sympathetic nerve fibers are activated, vasoconstriction occurs, which in turn leads to a decrease in blood flow, and the temperature of the human epidermis decreases due to the decrease in blood flow[56]. It has been shown that two emotions, anger, and fear, can be distinguished by skin temperature, especially the temperature of the fingers[37], [57], [58].

Cardiovascular-related physiological signal

The cardiovascular system contains all the organs of the body that control and regulate the blood system throughout the body. Cardiovascular-related physiological signals for emotion estimation studies mainly include heart rate (HR) and blood volume pulsation (BVP).

Heart rate is often used to identify positive and negative emotions [59], and other physiological signals, such as heart rate variability (HRV), can be derived from heart rate. HRV refers to the variation in heart rate cycle-by-cycle variability and has been widely used in adult psychiatric studies, such as stress tolerance [59], where HRV is suppressed when the participants is stressed and reappears when the participants is relaxed. Blood volume pulsation refers to the rhythmic pulsation of arteries in response to the regular systole and diastole of the heart as blood flows through the body. This type of signal can reflect certain cardiac and cardiovascular conditions in the body[60]. It has been shown through numerous experiments that changes in human emotions can also affect the changes in blood volume pulsation to a large extent. When a person is relaxed, the blood flow is smooth and there is a significant increase in the amplitude of blood volume pulsations, while when a person encounters stimuli and enters an emotional state of higher intensity, the frequency of blood volume pulsations is accelerated.

Heart Rate Variability–A healthy heart has healthy "irregularities". For example, if the heart rate is 60 currently, this doesn't represent for the heart beats 1 beat per second. Under such situation, the real situation may be that the interval between two consecutive heartbeats is 1.12 seconds, and the interval between two consecutive heartbeats is 0.86 seconds, but on average, it beats 60 times a minute. The HRV measures the irregularity of the heartbeat. If one's heartbeat is regular, then the HRV will be lower; if one's heartbeat interval is different, the HRV will be relatively higher. Generally, the higher the HRV, the better. This irregularity of the heartbeat is controlled by the autonomic nerves. The autonomic nerves in the human body regulate the functions of the body that are not participants to human subjective control, including heartbeat, respiration, blood pressure, and digestion. There are two types of autonomic nerves, the sympathetic nerves of "fight or flight" and the parasympathetic nerves of "relaxation or digestion". And HRV can reflect the working status of the autonomic nerves. If one is in the "fight or flight" sympathetic dominance mode, the HRV will be lower. If one are in a parasympathetic dominated mode of "relaxation or digestion," the HRV will be higher. Lower HRV means higher risk of anxiety, depression, and cardiovascular disease mortality. People with higher HRV generally have better cardiovascular function and anti-stress ability.

Wearable sensors for HRV measure–Nowadays the wearable sensor such as smart bracelets, rings and watches support HRV monitoring. In addition,There are apps such like HRV4Training to detect the HRV value which are through the main rear camera of mobile phone. Wearable smart devices can automatically monitor HRV. However, we apply app like HRV4Training to measure HRV, It is necessary to monitor is resting HRV. The specific operation is to spend one minute for the test every morning after user wake up and are quiet. It should be pointed out that there are multiple calculation formulas for heart rate variability. Different equipment has different calculation methods, and the measured results will be different. Moreover, HRV does not have an optimal standard interval, because it will be affected by many factors such as age, hormones, and lifestyle.

Respiratory signal–The process of respiration is the continuous exchange of air flow through the lungs in the human body, and the respiratory signal (Respiratory, RSP) measures the rate and volume of air flow through the lungs during this exchange. Resp-Rate and Resp-Amp are the two most common measures of respiration. Respiratory rate is accelerated when an individual is stimulated to produce increased emotion, while it slows down when the person is released to rest, but special cases can occur, such as when a person is suddenly startled and suddenly extremely stressed, where breathing may stop for a short time, and negative emotions may cause respiratory rate to become irregular[61]. While the depth of breathing is closely related to the heart function, deep breathing may bring about other physiological signals. Although the process of breathing is mainly gas exchange in the lungs, breathing causes changes in the heaving of the chest cavity so the sensors are fixed around the chest cavity when acquiring respiratory signals.

Chapter 3

The Evaluation of Bio-Emotion Estimation

3.1 Introduction

Tracing back to our goal in the chapter1, to reduce users' exposure to negative emotions while using social media, it is necessary to notify them when they are in a negative emotional state. In order to achieve this goal, it is necessary to apply an appropriate method to estimate the user's emotion state. In chapter2, we described some ordinary emotion estimation methods. Among them, Ikeda and colleagues combined psychological models and internal-information-based emotion estimation and proposed their novel method, which is named the bio-emotion estimation method. To evaluate the bio-emotion estimation method, they compared it with another emotion estimation method, "OKAO visiončiteOKAO, which estimates emotion with facial expression. Their study evaluates the method with an external information-based emotion estimated method.

3.2 Previous Research

3.2.1 Bio-emotion estimation method

EEG plays an important role in emotion estimation. However, multi-channel EEGs are generally too expensive and complicated to apply in daily life. Ikeda and colleagues[62], [63] proposed a method of estimating bio emotion based on the one-channel EEG and heart rate because the wearable heart rate sensor is inexpensive and easy to use. Nowadays, such simplified sensors have been applied to our daily life. Ikeda and colleagues applied the information collected with sensors to Russell's circumflex model[25] to estimate unconscious emotion with such simplified sensors. Russell's circumflex model[25] is known as a structure for classifying emotion. It has two axes: the vertical axis stands for arousal, and the horizontal axis stands for valence. Ikeda et al.'s research has advantages on both the sensor and model sides. In our research, we used the same method to estimate unconscious emotion.

Ikeda et al. applied two indexes on arousal and valence. For arousal evaluation, they used a combination of α and β waves from the brain. This index shows the activity stats of the central nervous and is used as the arousal value. In Russell's circumflex model, the vertical axis shows arousal in the positive direction and sleepiness in the negative direction[63]. They used an index that calculates from the heart rate variability (HRV) for valence evaluation. The HRV is based on the time-domain analysis. This index shows autonomic nerves for evaluating the sympathetic and parasympathetic states and is used as the valence value. In Russell's circumflex model, the horizontal axis in the positive direction is pleasant and unpleasant in the negative direction[63]. Both sensor values calculated to evaluate arousal and valence apply to Russell's circumflex model.

Also, in Ikeda et al.'s research, the accuracy of their emotion estimation method is shown by comparing their emotion estimation method [63]. Sugaya and colleagues also used the same method to estimate unconscious emotion. The model they used is in Figure3.1 [39], [40], [62]–[64].

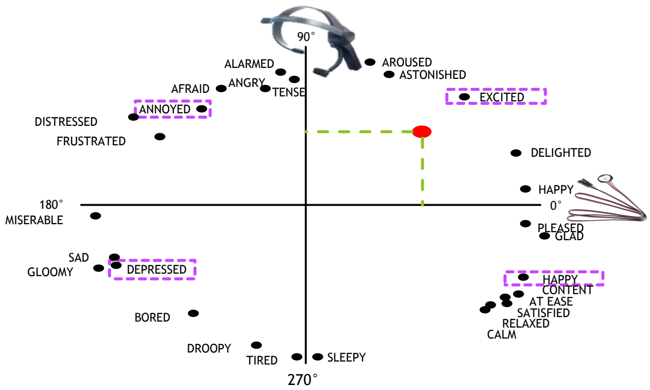

FIGURE 3.1: Russell's circumflex model applied with EEG and heart rate

3.2.2 Emotion evocation

The most basic condition for implementing emotion estimation experiments is to induce real, strong, and stable emotions in the participants. Many researchers use actors as participants[65], [66] because, compared to ordinary participants, actors are often well trained in emotional arousal and therefore have better speed, degree of arousal, and reversibility of emotions than ordinary participants. However, the most significant disadvantage of actors as participants is that they may over-exaggerate their responses for professional reasons, which is not consistent with the normal emotional arousal condition. Therefore, the research charger started to make a suitable selection from the material used to induce the participants[67]. Moreover, there are three main types of methods for emotional induction under laboratory conditions[68].

The first type is material evocation. As the name implies, this is the use of materials that have been selected to elicit emotions with a clear emotional arousal guide. These materials are often used in experiments, including visual, auditory, olfactory, and tactile materials. The most widely used visual and auditory materials include pictures, films[69], music[70], and text[71], such as the International Affective Picture System (IAPS) established by the

National Institute of Mental Health in the United States. Different types of material also have advantages and disadvantages; picture material is simple, rich contents, and easy to understand, but the duration of the emotions obtained by the stimuli is short, and there are limitations in the type and extent of emotions evoked. The film material can induce richer emotions and more extended emotional continuity. However, because the elements in the color film are too rich, the emotions evoked are more complex and not suitable for identifying and classifying discrete emotions. Music is simple, long-lasting, and can make emotions change in a short period of time. However, the disadvantage is that each individual has different aesthetics, tastes, and music preferences, so the analysis results are not standardized and lack a certain degree of universality. The textual material is specific and straightforward and is suitable for targeted discrete emotional arousal, but the disadvantage is that the degree of arousal is limited, and the arousal is not strong enough for recognition.

The second type of method is contextual elicitation with some emotional direction, which simulates an actual situation and allows the subject's emotions to change according to the manipulation of the researcher and consists of two main approaches. The biggest drawback of this method is that the expressions and movements are different from the actual scenes in daily life and cannot be reproduced well. Another way is the construction of simulated scenes to recreate the scenes that evoke emotions as much as possible[72]. The biggest disadvantage of this method is the high investment cost at the beginning of the experiment and the complexity of setting up the experimental environment.

The third method type is social situation evocation with certain emotion directional. One way is to ask the participants to recall their own social experiences similar to the specified emotional arousal situation, which can be a specific scene or a specific event, to induce the corresponding emotion[73]. Another approach is to have multiple participants engage in social discussions, making the emotion-evoking environment closer to real life[74]. The last method is a social psychological approach that uses social stories with obvious emotional pointers to elicit emotions in participants[75]. The biggest disadvantage of this method type is that the individual variability of the participants can influence it. Different participants have different emotional responses to the same social environment or social event because of their different interests, personality, and upbringing, which is not conducive to integrated research. The above methods include the most common ways of eliciting emotions in current emotion estimation studies, and in subsequent experiments, we select the elicitation materials according to the purpose of the experiment.

Aroma

The aroma can cause differences in reactions on bio-signals. Since aroma can affect the bio-signals, aromas such as lavender ylang-ylang are proved to decrease the brain's activity. However, such stimulation has not been found as related to emotions. Therefore, we proposed to use aroma as stimulates used the self-assessment manikin (SAM) as a subjective questionnaire to evaluate whether the bio-emotion estimation method is effective

Effects of aroma on the autonomic nervous system

Yoshida et al.[76] examined the effects of essential oils on autonomic nervous system function using electrocardiogram, skin blood flow, skin electrical resistance (GSR), and blood pressure of participants, focusing on Lavender, Rosemary, and Citronella, the three most frequently used essential oils used in many studies including their effects on mental and psychological aspects. The effects on autonomic nervous system function were examined in the experiments using the essential oils. In the experiment using the essential oil, 10 cc of water and 6 drops of essential oil (3% solution) were put into the aroma pot immediately after leaving the room and heated for about 10 minutes to release the aroma into the room. The aroma was continuously emitted during the experiment. The subject moved to the room filled with aroma, quickly attached the electrodes of each measurement device, and inhaled for 10 minutes in a resting sitting position. The aromatic pot was placed 30-40 cm away from the subject's nose, and the room was ventilated for 60-70 min after inhalation of one aroma. The participants left the room in the control experiment and re-entered after 10 minutes. In contrast, Rosemary, which was perceived as refreshing, temporarily stimulated the sympathetic nervous system. In addition, scents with individual preferences, such as citronella, had complex effects on the autonomic nervous system.

Autonomic nervous system activity and brain activity by aroma

Duan et al.[77] examined the effects of lavender aroma on the autonomic nervous system and brain activity. As physiological indices, brain accumulation was measured by positron emission tomography (PET) and LF/HF, which can display heart rate variability. The scent was presented in the form of a scented poultice for 10 minutes. There was no significant change in brain activity overall, but there was an increase in activity in the left posterior cingulate gyrus (x–6, y51.z28) and a decrease in activity in the right temporal lobe (Superior Temporal Gyrus, x48, y51-14) in lavender. There was no change in the mean systolic or diastolic blood pressure after 10 minutes of lavender load compared to the control. In terms of heart rate, HF was significantly higher, but LF/HF was significantly lower, during lavender stress. HF increased after lavender aroma, but LF/HF decreased after lavender aroma. This suggests that lavender aroma may have the effect of inhibiting sympathetic nerves first and then increasing vagal nerves.

Effects of aroma on EEG activity

Masago et al[78] examined the effects of Lavender, Chamomile, Sandalwood, and Eugenol aromas on EEG and subjective perception. Twelve channels (F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T5, and T6) on the scalp were measured as physiological indices based on the international 10-20 method. From each channel, θ (4-8 Hz), $\alpha 1$ (8-10 Hz), $\alpha 2$ (10-13 Hz), and β (13-30 Hz) were analyzed. The aromas were presented for 90 seconds with the device fixed on the subject's chest, about 15 cm below the tip of the nose, and there was a significant change in the EEG activity of $\alpha 1$ after receiving the aroma.

The aromas used in this study did not have a significant effect on $\alpha 2$, θ, and β. A significant decrease in $\alpha 1$ was observed in the left parietal (lavender: $p < 0.01$, eugenol: $p < 0.01$, chamomile: $p < 0.01$) and left posterior regions during the 10 seconds immediately following aroma inhalation. In this study, there were significant changes in $\alpha 1$ activity during aroma inhalation. α-wave activity usually corresponded to some sensory stimuli in addition to olfactory stimuli[62]. Lorig mentioned[25] a topographic map that may clearly show the differences obscured in the table of EEG values. Significant probability mappings[64], such as t-maps, are often used for EEG changes during stimulation or working states, compared to changes during resting states. by using $\alpha 1$ t-maps, we obtained several types of patterns corresponding to each odor.[78]

Influence of aroma presentation on immune function after stress loading

Uchiyama et al.[11] examined the anti-stress effect of aromas using Secretory Immunoglobulin A (SlgA), one of the immunological indices, after mental stress loading by addition work. The profile of mood states (POMS) was used to evaluate the psychological state, and the degree of stress load was determined by analyzing fatigue (F). Heart Rate (HR), Systolic Blood Pressure (SBP), and Secretory Immunoglobulin A (SIgA) were measured as physiological indices. One drop (about 0.05 ml) of a highly concentrated stock solution of 98.3% purity was dropped onto a moquette and presented after 25 minutes of stress, and at the same time, essential oil (50%) diluted in vegetable oil was applied to the inside of both wrists. The presentation time of the scent was about 2 minutes to allow for olfactory adaptation. HR and SBP increased during the workload, suggesting that the scent induced a predominant effect of sympathetic nerve activity as the stress load caused considerable tension and fatigue in the participants.

3.3 Proposal

During Ikeda and colleagues' research, they applied the facial expression-based emotion estimation method as the comparison to evaluate their bio-emotion estimation method. The facial expression estimate result was provided by a commercial software called OKAO Vision. However, according to Pérez Rosas and colleagues' research[79], the OKAO vision has an accuracy of about 61.04%. During Ikeda's evaluation of the bio-emotion estimation method, they didn't consider the possibility which the OKAO vision could provide an incorrect emotion estimation result.

Also, during the evaluation of the bio-emotion estimation method, Ikeda and colleagues conducted the experiment, which used several funny videos as stimulation to evoke participants' emotions. Emotion evocation by video is classic in emotion estimation research. However, when applying the video as the stimulation, most of the research is applying the standard emotion evocation database(such as LIRIS-ACCEDE[80], CAAV[81]) as the stimulation. During the evaluation of the bio-emotion estimation method, the applied video was selected based on the author's subjective opinion. This stimulation may lead to the problem that participants' emotions are not evoked or that the evoked emotions are not sufficient enough to occur facial expression. On the other hand, the previous research above shows that aroma is an effective way to evoke emotion. Also, the emotion evokes by aroma has a few individual differences in emotion. Therefore, we considered using aroma as the stimulation to evaluate the bio-emotion estimation method. As for the comparison, instead of the facial expression-based emotion estimation, we consider applying a classical way to represent participants' emotions. One of the classical ways to use a non-verbal self-report questionnaire to evaluate emotion which is the self-assessment manikin questionnaire(Fig. 4.1). The SAM scale asks participants to report their emotions with a non-verbal scale with nine levels. The SAM scale includes arousal, valence, and dominance. To match with the bio-emotion estimation method, we only apply arousal and the valence scale in this part of the research. Therefore, in this chapter, we propose to apply aroma as the stimulation to evoke participants' emotion to collect the bio-emotion estimation result, and apply the SAM scale to collect the self-report of participants. Finally, to evaluate the bio-emotion estimation method, we compare the estimation result with the SAM result.

3.4 Method

3.4.1 Sensing method

Based on Ikeda et al.'s research, two types of sensors were used. First, as one of the HRV indexes, pNN50 was measured using heart rate sensors. Here, we used the sensor "Pulse Sensor Amped" [82]to detect pNN50 as the valence value. This sensor uses power with a 4 mA current at 5V. It also combines a simple optical heart rate sensor with amplification and noise cancellation circuitry, making it fast and easy to acquire reliable pulse readings. Second,

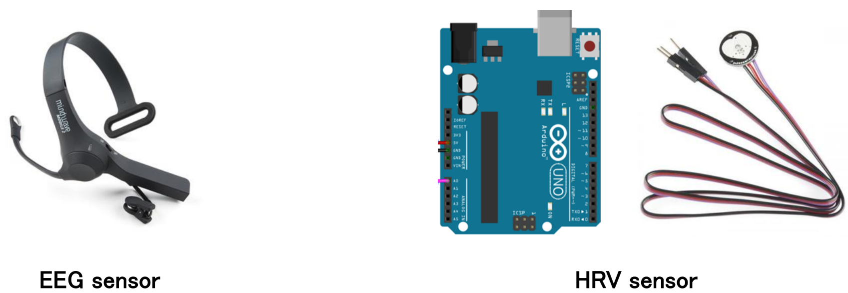

FIGURE 3.2: Sensors used in the experiment

Highα and highβ waves are measured by EEG sensor. Here, we applied the Neuro Sky's "Mind Wave Mobile" sensor[83] to calculate the arousal value, which is the difference in intensity between Highα and Highβ signals. It consists of a headset, a sensor arm, and an ear clip. The headset's reference and ground electrodes are located on the ear clip, and the EEG electrode is on the sensor arm, where it rests on the forehead above the eye (FP1 position).[83]

3.4.2 Accuracy

To evaluate the bio-emotion estimation method, We applied the classical subjective evaluation Self-Assessment Manikin(SAM) as the "correct answer" to evaluate the accuracy of the bio-emotion estimation method. Based on the sensing method, we collated the 'Attention-Meditation' as the arousal. Also for reference, we also collected the High β/ High α to match the arousal. For the valence index, we decided to continue with the pNN50 as the valence from the original evaluation of the bio-emotion estimation method.

TABLE 3.1: The accuracy of each index

SAM Result	Bio-emotion Result	Situation	Abbrev
Positive	Positive	True Positive	TP
Positive	Negative	False Negative	FN
Negative	Positive	False Positive	FP
Negative	Negative	True Negative	TN

To evaluate the bio-emotion estimation result, we compare the bio-emotion estimation result with the SAM result separately. When the estimated bio-emotion result is the same as the SAM result, we assume it as a true situation, otherwise as a false condition. Also, when the estimated bio-emotion result is positive, we assume it as a positive situation, otherwise as a negative situation. For instance, when participants report arousal is increasing compared with the neutral condition, we will mark the SAM result as positive. When the bio-emotion represent for arousal is increasing, we also mark the bio-emotion result as positive. While both of the results are positive, we mark such situation as a "True Positive". All situations is shown in the Table 3.1. Basing on this method, the accuracy is calculate by the equation 3.1:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3.1}$$

3.5 Experiment

In the experiment, we set the experimental environment contain as a room temperature to avoid the influence of discomfort caused by unrelated factors. Also, to avoid the influence of unexpected aroma in the experiment environments, we asked all participants to wear no aroma before and while experiment. In the meantime, we kept the experimental environment without strange odor. In this experiment, our experiment is including nine participants(N=9). All participants are from Japan. Among nine participants, six male and three female are involved.

Next, for the emotion evoke stimulation, based on the previous study we introduced above, we choses five aroma to represent different kind of emotions. The aroma we used in the experiment including five different types, which are the dimethyl disulfide (DMDS), ylang-ylang, peppermint, jasmine, lavender. Each aroma has the concentration of 10%. Each aroma representing for is shown in the Table3.2. Also, the aroma we used is shown in the table below: the aroma we selected stand for three different emotion state, which includes negative, neutral, positive.

TABLE 3.2: The aroma applied in the experiment

No.	Name	Concentration	Emotion
1	Dimethyl disulfides (DMDS)	10%	Negative
2	Ylang-ylang	10%	Neutral
3	Peppermint	10%	Neutral
4	Jasmine	10%	Neutral
5	Lavender	10%	Positive

With the material we conducted preliminary experiment. The procedure of the experiment is shown is the Figure 3.2. First, we require a rest time of sixty seconds. During the rest time, the participants are asked to remain a relax position. After rest time, one of the aromas is presented as the stimulation to the participant for sixty seconds. It is important to notice that we had the DMDS stimulation only for thirty seconds. Since the DMDS is too strong for the participants, to avoid the influence we also present DMDS as the last stimulation. After exposed to the stimulation, another rest time for sixty seconds is token. After the second rest time, the blank time for sixty second is taken. The procedure above is for one aroma. Such procedures are repeated for five times with different aroma randomly for each participant.

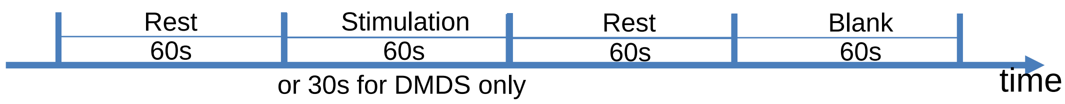

FIGURE 3.3: Procedure of the experiment

3.6 Result

The Figure 3.4 shows the transform of emotion to each aroma. Basing on the idea of the bio-emotion estimation, we mapped the transformed average for each aroma in Figure3.4. The arrow shows the transform direction,and the points show the position of average value during different stage. According to the experiment procedure, each aroma has three stages which includes before, while, and after the stimulation. The Figure3.4 shows that the lavender keep decreasing the arousal and increasing the valence of bio-emotion. And the DMDS keep increasing the valence and increasing the arousal overall.

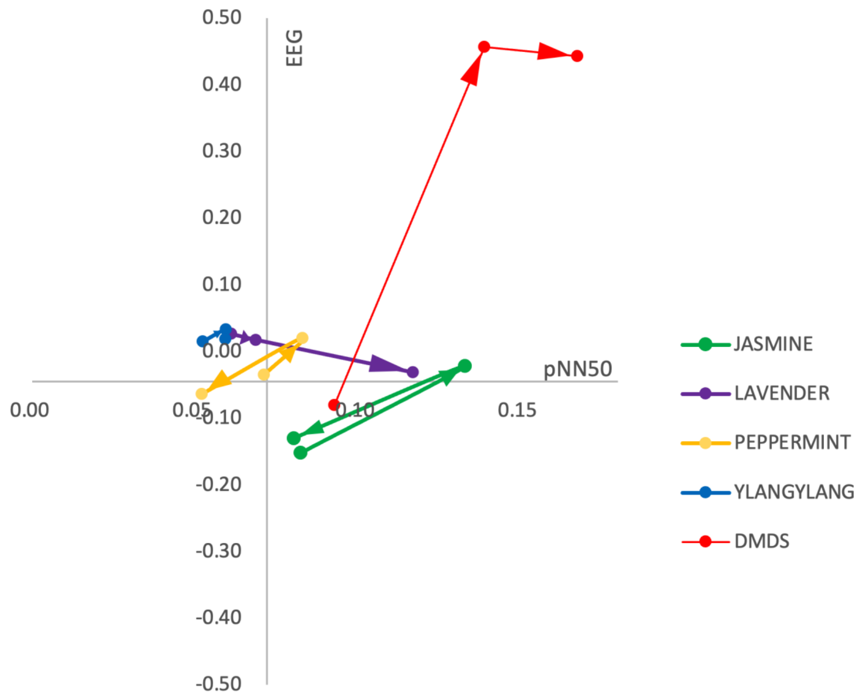

FIGURE 3.4: The transform of emotion state to each aroma

The Figure3.5 shows the average result of the SAM and raw data to each aroma. As the result, it is shown that during all five types of aroma we provide, four types of aroma are matching the transform direction with SAM result, except the DMDS. Even the arousal of bio-emotion is kept consistent with the arousal of SAM. However, contrary to common sense, the DMDS increased the bio-emotion's valence value pNN50, while the valence of SAM shows an extremely low level. The bio-emotion estimation to DMDS earned an opposite result with the SAM result. This might be because the 10% 30s stimulation of DMDS is still over strong for the participants. This caused the heart rate to increase in a short time, thus the heart rate variability index pNN50 also increased. This might be the reason that the bio-emotion estimation method has an opposite result with SAM[28]. Based on such results, we assume that aroma could be used for different emotion-evoking. However, it is still worth attention when evokes negative emotion.

3.7 Discussion

During the experiment of the evaluation of the bio-emotion estimation method, we applied the aroma as the stimulation to evoke the emotion of participants and the SAM scale to evaluate the subjective emotion of the participants. During Ikeda's research, they applied attention-meditation as the arousal index. However, the value of attention and meditation are calculated by the origin algorithm.This algorithm was provide by the EEG sensor company NeuroSky,and the attention and meditation value was calculated by a black box method. As a reference, we conduct anther index as the arousal

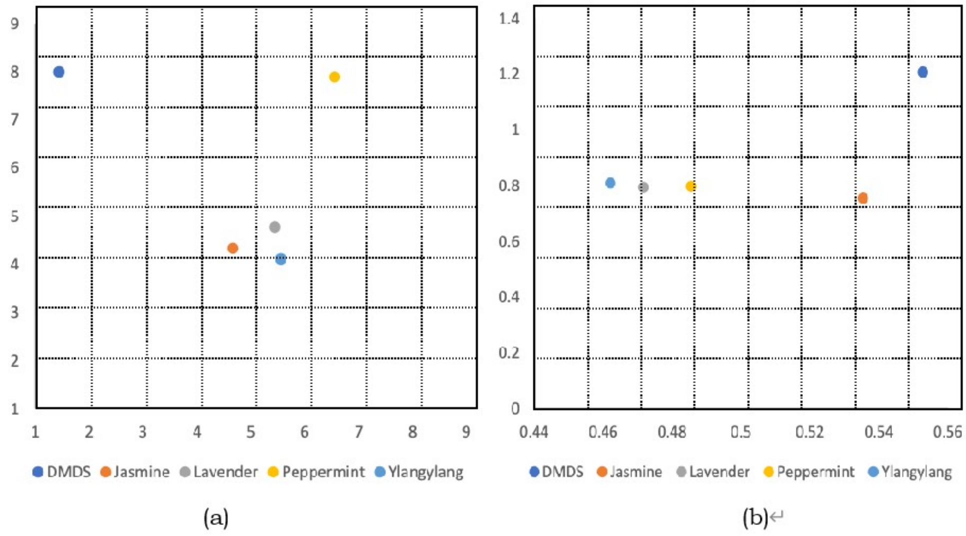

FIGURE 3.5: The average of (a)SAM, (b) Raw data

which is the β/α. This index applied as the arousal during several research such as Umezawa[84] and Hirai[85]. According to their research, the β/α also has a good performance on represent the arousal index.

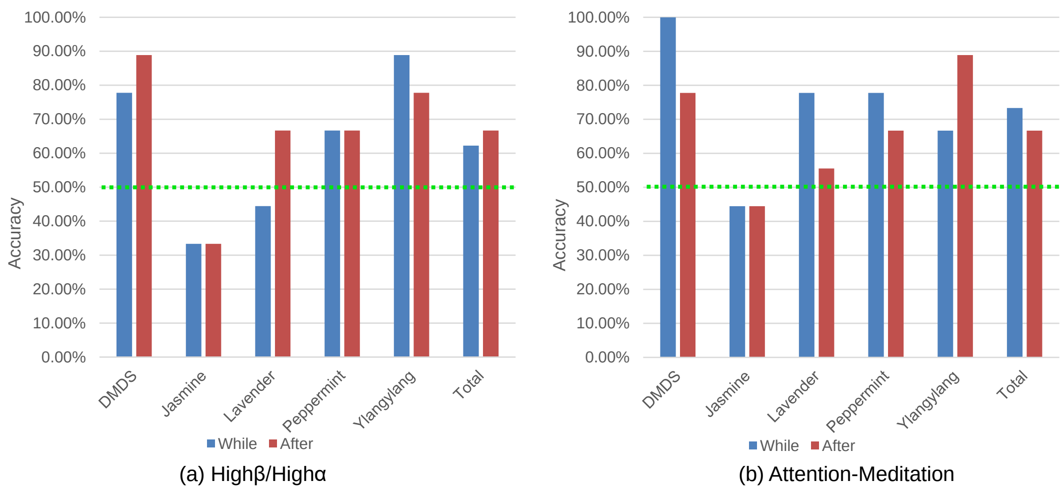

FIGURE 3.6: The accuracy of arousal(a) Highβ/Highα, (b) Attention-Meditation

Basing on the method we introduced in section 3.4.2, we compared the bio-emotion estimation method with the SAM result, and the accuracy of estimated arousal is shown in Figure 3.6, and the accuracy of estimated valence is shown in Figure 3.7. We mark the 50% as the green dotted line, the blue bar represent for the accuracy during stimulation and the red bar represent for the accuracy after the stimulation.

First, for the estimated arousal, the attention-meditation get a higher accuracy than the Highβ/Highα under while stimulation condition. We consider that the attention-meditation could be a better index to represent the arousal value in bio-emotion estimation method. When compare the influence of different condition, Highβ/Highα had a higher accuracy after stimulation, while attention-meditation had a higher accuracy while stimulation. Also, the accuracy increased after the stimulation. Surprisingly we found the Highβ/Highα matches the reaction with the pNN50. It is well-known that the pNN50 is related with the autonomic nerves system, it is obvious that the pNN50 changes got a higher accuracy on the condition of after stimulation. Basing on such situation, we suggest the future work to consider about the timing when combine the different index together in one model. Also, with the accuracy of the arousal index and the valence index, we applied the bio-emotion estimation method with the biofeedback to inform users of their bio-emotion.

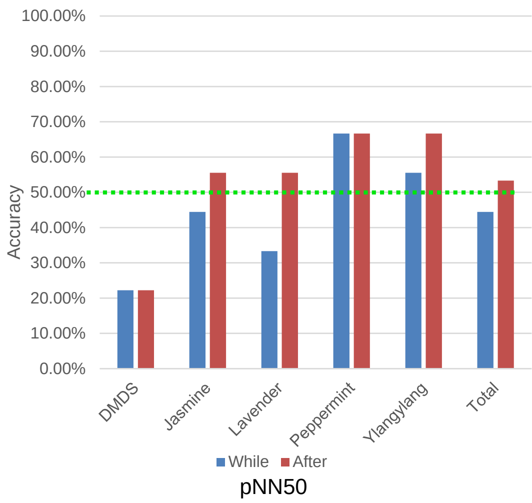

FIGURE 3.7: The accuracy of valence compared with pNN50

Chapter 4

Biofeedback

4.1 Biofeedback

Most biofeedback on mental disease treatment is rely on the autonomic nervous system related physiological changes. The autonomic nervous system can divide into the sympathetic and parasympathetic nervous system. The balance of sympathetic and parasympathetic nervous system can relate with tense and relax of human, therefore most of the biofeedback treatments are applying the physiological changes occur with the activity of different part of autonomic nervous system. For example, the activity of sympathetic can cause the anxiety and the increasing of muscle tension which can be detected with electromyography (EMG)[86]. Recently EEG biofeedback has also been used on the treatment. Except EEG, the fMRI can show the activity of area of brain. After detecting the physiological changes, the feedback is also important to the treatment. Normally, the feedback includes the audio stimulation[87], the visual stimulation[88]–[90] and the fusion stimulation[91], [92]. First the audio stimulation on biofeedback. The biofeedback uses pure tone to inform the participants of their physiological changes.[93] Next, among the research applied the visual stimulation, the graphic changes related to physiological changes is shown to the participants. For example, In the[90] when the EMG decrease, the object on the display will turn green. In[89], the light spot is moving up and down in rhythm of RSP, is worth to mention that during the fusion stimulation biofeedback, there are serious game basing on biofeedback with makes a huge contribute to the treatment of mental disease.

4.2 Evaluation of biofeedback

The measurement to biofeedback is divide into physiological measurement and the psychological measurement. The psychological measurement is mainly by the questionnaire. After the participants are stimulated by the emotion eliciting material and the corresponding emotion is induced, the valence and reliability of the emotion elicitation must be ensured. The effect of emotion elicitation is influenced by multiple factors, such as individual differences in participants, the sequence of experimental materials, and the experimental environment. Therefore, after collecting physiological data from participants, the valence of the experiment needs to be verified. The methods used to assess the effect of emotion elicitation include participants' self-assessment reports, emotion scale tests, and interview transcripts conducted with participants. At the same time, the assessment of the emotion evocation effect should be conducted immediately after the end of the emotion evocation experiment so as to ensure the timeliness of the assessment. In terms of effect assessment through affective scales, the more commonly used affective scales include self-report assessment, PAD scale, SAM scale, etc. The Self-Report Assessment is a report in which the participant assesses the extent of several basic emotions, each of which is divided into five or, more carefully, nine levels. For example, if there are 5 levels of happy, not happy at all is defined as 1, mild happy is defined as 2, moderate happy is defined as 3, strong happy is defined as 4, and very strong happy is defined as 5, then the participant is asked to choose a value from 1-5 to describe his or her emotional state when performing the self-report assessment. The advantage of the self-report assessment is that it is a good way of describing the emotional state of the subject. The advantage of self-report assessment is that it is intuitive and easy to understand, while the disadvantage is that some mixed emotions cannot be described by this method.

The PAD scale is based on the three-dimensional model of emotion, and the three letters of the PAD are the three dimensions of the three-dimensional model of emotion, P for Pleasure, which is the positive and negative nature of emotion, A for Arousal, which is the degree of activation of emotion, and D for Dominance, which is the degree of control over the situation or others. The degree of control over the situation or others. The PAD space can be divided into eight sub-spaces using the PAD as the three axes, and each axis is mapped to a range of when evaluating emotion, and specific emotional states are measured in one dimension by a pair of emotion words with opposite emotional states while limiting changes in two of the three dimensions. The original PAD scale contains 34 pairs of affective evaluation items, of which the P dimension contains 16 evaluation items, and the A and D dimensions contain 9 evaluation items each.[94]

The SAM (Self-Assessment Manikin) scale1 is actually a graphical representation of the PAD scale, which uses visual images to graphically display the three dimensions of the PAD scale. People can evaluate their own emotional state by directly selecting the picture that is closest to their own feelings. Figure4.1 show the graphs included in the SAM scale. The first row of the graph shows the evaluation of pleasantness, in which the cartoon character's expression changes to reflect the change of pleasantness, with a gradual transition from an unhappy frown and a downward curved mouth to an upward curved mouth indicating a happy expression. The third row shows the dominance of the cartoon character in terms of size. Overall, the SAM scale is intuitive, but the specific meaning of the pictures may take time for humans who are new to emotion evaluation with the SAM scale to understand. Given the complexity of emotions, there is no uniform standard for evaluating the effect of eliciting emotion, as there is a tendency for the approaches and methods to be diverse when assessing the effect elicited by emotion-evoking material. It is important to try to use a standardized library of emotion-evoking materials when conducting research so that the evoked effects remain consistent and can be easily compared and analyzed.

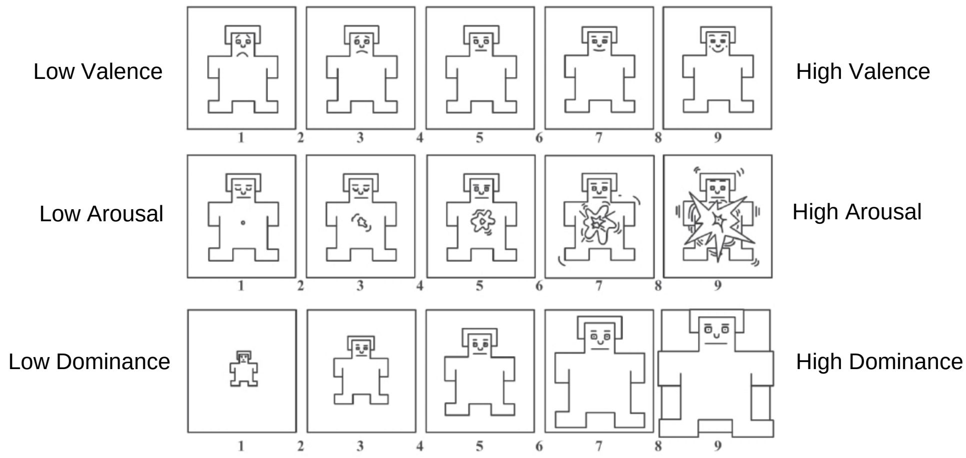

FIGURE 4.1: The self-assessment manikin questionnaire[95]

4.3 Emotion with biofeedback

The emotion feedback is one branch of biofeedback. In this section we introduce related research of biofeedback which include the physiological signals and the form of biofeedback. The idea of the biofeedback mechanism comes from the area of medication. One of the first studies was carried out by Mandler et al.[96], They defined biofeedback as "the relationship between autonomic response and the participants' reported perception of such response-induced stimulation" and denote it as an autonomic response. On the basis of this definition, biofeedback has been applied in therapy. For example, when unconscious physiological changes occur, patients can get feedback such as lighting or sound to help them realize their unconscious physiological changes. In the meantime, due to the emotion change are occur with physiological changes, the biofeedback has been applied to treatment of some mental disease. Furthermore, biofeedback has been applied on daily usage to help user to maintain mental health.

Chapter 5

Biofeedback with Bio-Emotion Estimation

5.1 Introduction

In the first chapter, we discussed the context of social media usage and the problems caused by social media usage. Our proposal is to detect users' emotion states and inform users of their own emotion states to provide users from replying to negative content under negative emotions.

In order to realize the above proposal, we subdivide the problem into two. One is to detect the user's bad state, and the other is to give feedback to the user about the bad state. For the first problem, in Chapter 2, we studied the existing sentiment detection methods and metrics and selected Ikeda's sentiment detection method as the basis for our sentiment detection. For question 2, we discuss the subjective of emotion feedback, the student feedback, as a starting point. Based on the discussion, we propose our improvement method. As an existing problem, first Ikeda's study has not been fully validated, and second the acceptance of users of the emotion feedback method that incorporates somatic emotion speculation is unknown. To address problem 1, we propose to use Aroma, which evokes the corresponding emotion, as experimental material to verify the valence of Ikeda's method of somatic emotion inference. For problem 2, we built a simple prototype as the material for the preliminary experiment 2. According to the design of the experiment, we invited participants to experience the system. In order to verify the user's acceptance of emotional feedback, a questionnaire was also administered to the participants. In this chapter, we will address the two preliminary experiments described above. The results of these experiments will be analyzed and discussed.

5.2 Proposal

Ordinary, the internal information is sensing physiological changes of humans. Emotion estimation using internal information has been extensively researched. Since humans are unable to influence physiological changes such as electroencephalogram and heart rate, emotion estimation based on biological information can objectively estimate true emotion. A survey on emotion estimation using the EEG is presented by Alarcao et al. Their research described the survey of emotion estimation with EEG signals. For several years, the EEG has been utilized to evaluate bio-emotion since such bio-emotion could be unnoticed by humans. The bio-emotion estimation method based on the EEG has been employed in the majority of studies. Because multi-channel EEG is often too expensive and difficult to use in everyday life the wearable heart rate sensor is affordable and simple to use, Ikeda and colleagues, [62], [63] proposed a method of estimating bio-emotion based on not only the one-channel EEG but also heart rate. The use of such a sensor is now commonplace in our daily lives. Ikeda and his colleagues. Russell's circumflex model[25] was used to predict bio-emotion using the information from biological sensors. Russell's circumflex model[25] is a methodology for categorizing emotions. It is divided into two axes, with the vertical axis representing arousal and the horizontal axis representing valence.

The bio-emotion estimation method fits our goals. To detect bio-emotion, Ikeda et al. propose using EEG and heart rate sensors. On Russell's circumflex model[25], they utilize the two-dimensional coordinates of "emotional expression," "pleasant-unpleasant," and "arousal-drowsiness." They proposed a strategy for deepening emotional self-understanding by exhibiting bio-emotion.

We introduced the related works on the biofeedback closed-loop model in chapter 4, as for the detail of applied biofeedback into emotion regulation with is the emotion feedback research. As for applying biofeedback from the psychology treatment to maintain a healthy mental state, there is research that applied biofeedback in stress management. Moss and Gunkelman suggested biofeedback as a technique to improve health and performance by measuring an individual's physiological activity and thus supporting humans to change it[97].

Based on the model in Figure5.1, researchers combine biofeedback with psychotherapy in order to help users with emotional state stabilization. Janssen et al. developed an affective music player (AMP) to change the users' mood employing music[61]. In their research, the mood was determined from the user's skin temperature because the skin temperature is related to the valence of the user[37], [57], [58]. As a result, it might not be necessary to continually infer affective states from physiological signals, which is often the approach taken in affective computing applications. Continuously inferring affective states from physiological signals is a very challenging process and adopting a biofeedback closed-loop helped to overcome this problem.

As we introduced above, emotion feedback is normally used in e-learning and psychological therapy. In the case of e-learning, students' emotion is estimated and feedback to the teacher in order to help the teacher to adjust the teaching strategy. However, the feedback doesn't presented to the students themselves. On the other hand, during psychological therapy, the feedback is directly related to the change of physiological signals. Also, in order to take such therapies, it is necessary to attend the excise of using such a system before the formal therapies. This makes the emotion feedback hasn't been applied to daily usage. The acceptance of such a bio-emotion feedback

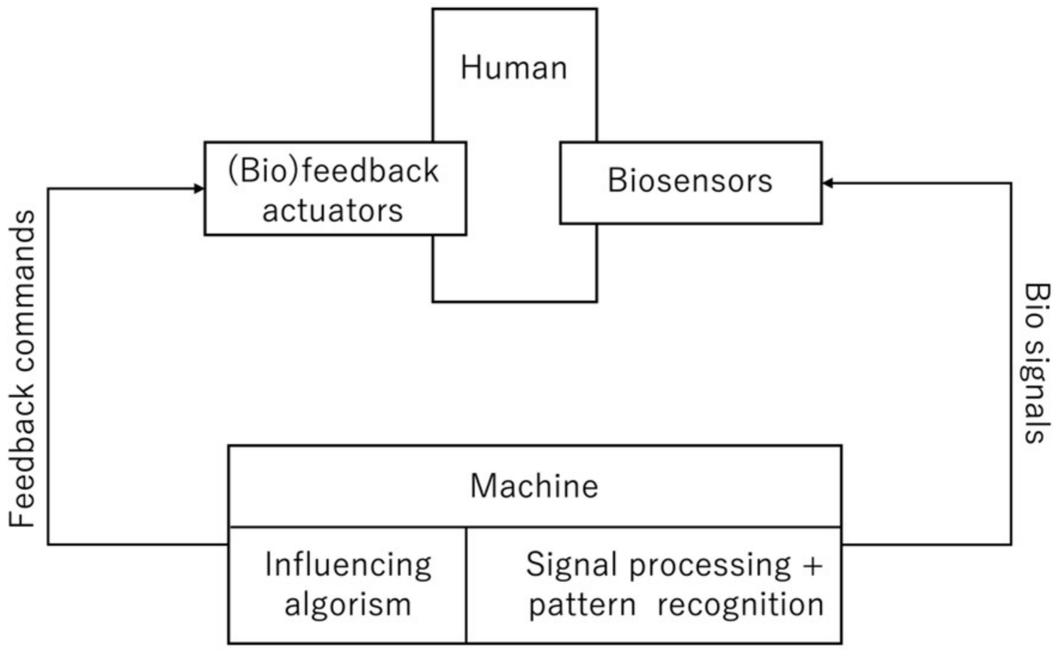

FIGURE 5.1: General biofeedback closed-loop model[96], [97]

method is unknown to ordinary users. Therefore, we proposed to conduct subjective research on the bio-emotion feedback method. To verify the effectiveness of the proposed system, a comparative experiment was conducted. In the experiment, we hypothesized a situation for users. In this situation, users were asked to recall their emotions during the experiment and express their emotions in simple words. In the meantime, with the biological sensors, we could detect the bio-emotion during the emotion recalling. Lastly, we developed a system to compare the expressed emotion and the emotion detected using the biological sensors and gave feedback on the mismatched results to the user. The effectiveness of the system was evaluated through the use of a questionnaire.

5.3 Subjective Evaluation

In section 3.2, we discussed the effectiveness of the bio-emotion estimation method. And found out that the bio-emotion estimation method could provide emotion estimation of dividing emotion into four detentions. However, whether such a method could be accepted as the emotion feedback is not clear. Based on the remaining problems, we conducted the preliminary experiment on the research of user's reaction on the emotion estimation method.

5.3.1 Experiment

As the procedure of the experiment. Firstly, we asked the participant to wear the electroencephalogram sensor and the heart rate sensor. After the experiment starts, we ask the participant to rest for one minute. And the recorded sensor value will be used as the baseline. Next in order to evoke the emotion of the participants we asked the participant to recall their own similar experiences while they are reading one of the scenarios (from novels). During the reading task, the sensor will keep recording participants' EEG signal and the pNN50 signal. After the reading task, the participants were asked to input their emotions with the re-presentable emotion word. The system compared the estimated emotion with the participants' declared emotion (participants' input) and feedback on the result to the participants. After the experiment, a questionnaire survey was carried out. In this experiment, there were 24 participants (9 males and 15 females) divided into two groups the group with feedback and the group without feedback.

5.3.2 Results

We analyzed the 24 participants' data after excluding invalid data of two participants (females), since the low stability of the sensor when worn. Using the results of this experiment, we conducted a paired t-test on the items of the questionnaire in Part 1. The results are shown in Table5.1.

TABLE 5.1: Results of statistical comparison by paired T-test

Comparison item	P-value
The motivation for advice about emotional expression	0.01(*p < 0.05)
Unpleasant experience	0.20
Hesitation before in expressing feelings	0.13
Motivation to use the system	0.03(*p < 0.05)

A significant difference (*p < 0.05) between the groups with feedback and the group without feedback was found for the motivation for advice about emotional expression. As for the result of the "willing to use the system" item, the group with feedback was significantly higher than the group without feedback (*p < 0.05). There was no significant difference in the "unpleasant experience" and "hesitation before expressing emotions" between the two groups.

Next, in Part 2, free descriptions of several opinions were obtained from the participants, including whether knowing their emotions enabled them to not only correctly express their feelings but also deepen their awareness of themselves.

5.3.3 Discussion

In this chapter, we described our preliminary experiment. The first experiment is to evaluate the effectiveness of the bio-emotion estimation method.

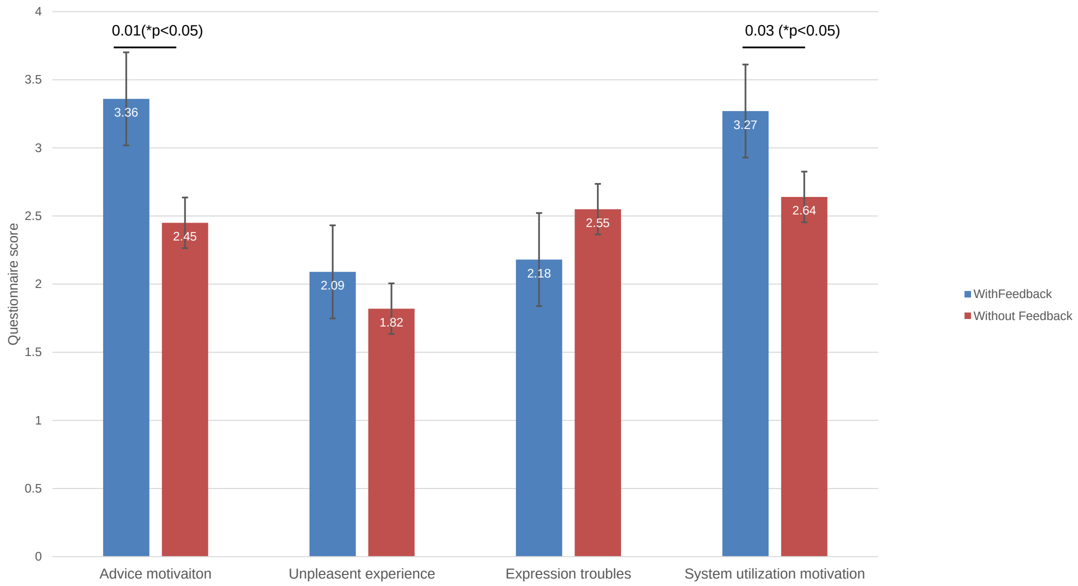

FIGURE 5.2: The average of the questionnaire result

Also, the result shows us that, based on the result of the questionnaire we find out that, after using the bio-emotion feedback system, the user has more preference of getting suggestions before expression. The significant difference shows bio-emotion feedback system could be accepted by the users. According to the participants' interview, we found that as the emotion-evoking, the selection of novel clips is subjective and sometimes couldn't evoke participants' emotion. On the opposite, the participant who had a similar experience with the novel clip reported that their emotion is evoked easily while reading the novel clip.

5.4 Bio-Emotion Feedback in period time

5.4.1 Background

The use of social media has been increasing year by year, but the problems caused by misinformation on social media cannot be ignored. A huge number of negative information on social media is misinformation and hate messages. Since the misinformation and hate messages could lead users to an extreme and negative emotion state. While users are under extreme and negative emotion state, they are more inclined to reply to such content with negative expression or share this negative information. Such behaviors could cause the increasing and the spreading of negative information, and more users could be affected and lead to extreme and negative emotion states. Therefore, we proposed to alert users to their negative emotion state, in order to prevent users reply or sharing negative information. To address this problem, we made a proposal which is (1) to estimate users' emotion state and (2) to give the user feedback of their estimated emotion state. For this method, there are two issues the first is Emotion estimation and the second is emotion feedback.

For the first issue emotion estimation, recently, research of emotion estimation plays an important role in human-machine interaction. Depending on the procedure of how emotion occurs, the emotion estimation could be divided into two types of categories: a). External information-based emotion estimation; b). Internal information-based emotion estimation. First, the external information-based emotion estimation uses the emotion-related external changes, such as facial expression, gestures, speeches, etc. Second, the internal information-based emotion estimation method uses the internal changes of humans. Such as EEG, HRV, HR etc. When applying emotion estimation to social media usage, we need to consider the changes that happened to the users while using social media and under a negative emotional state. While using social media, normally, users view the contents in a short time. Also, when using social media, even user is under a negative emotional state, obverse external changes such as facial expressions, gestures, or speeches do not happen in the meantime. Therefore, it is hard to apply the external information-based emotion estimation methods to estimate the user's emotional state while using social media. On the other hand, the internal information-based emotion estimation method can detect the emotion-related physiological changes of the user. Furthermore, daily wearable sensors can detect physiological changes, which is easy to apply to normal usage. Among internal information-based emotion estimation methods, Ikeda and colleagues proposed a bio-emotion estimation method that combines physiological signal and psychological model to estimate user's emotional state. The psychological model they used is the 2D arousal-valence model. This model divides the emotional state into four quadrants by arousal axes and valence axes. In the bio-emotion estimation method, Ikeda and colleagues applied one of the heart rate variability indicators, pNN50, to valence axes and applied one of the Electroencephalography (EEG) indicators to arousal axes. With the combination of two types of physiological signals above, based on the 2D arousal-valence model, their method has the advantage of real-time estimation of emotional state. Therefore, we proposed to apply the bio-emotion estimation method to social media usage to detect emotional states.

For the second issue emotion feedback, emotion feedback is developing as one branch of biofeedback. Biofeedback is a therapy that alerts users with their unrealized physiological changes to train users to gain the ability to regulate their state. With the development of biofeedback, there are more research appeared. Since the emotion occurs with physiological changes, Zhonglin Li and colleagues used emotion feedback to help users regulate their emotional state. Linping Shen and colleges applied emotion feedback to e-learning[98]. Such research is mainly used in medical and e-learning applications. However, the application of this method has not been fully investigated.

Based on the issues above, we proposed to combine bio-emotion estimation with emotion feedback as bio-emotion feedback. We assume that the bio-emotion feedback could elicit the emotion regulation of the user. Basing the hypothesis, we conduct a preliminary experiment. The preliminary experiment aims to feedback the difference between users' bio-emotion and their emotions. After the experiment, we had a statistical analysis of the result. Based on the result, we found out: 1. Alerting the feedback to users at different timing could change the effects of bio-emotion feedback; 2. The bio-emotion feedback is more effective while the user is under a negative emotion state; 3. The distribution of users' states is enormous while they are alerted by the feedback content of their bio-emotion.

5.4.2 The Period time feedback system

The results of the previous works mentioned above imply that biofeedback is generally used in therapy, but rarely in daily applications. Meanwhile, biofeedback does not usually correspond directly to emotions. The biological information-based emotion estimation method can estimate bio-emotion. Here, we propose to combine biofeedback with the biological-information-based emotion estimation method and apply it to social media. The remaining issues of previous research are discussed in the last section. In order to apply both bio-emotion estimation and emotion feedback, based on the issues above, we clarified the purpose of the experiment. In this experiment, we are aiming to evoke the user's emotion firstly. And then detect the user's bio-emotion state with the bio-emotion estimation method.

We hypothesized a situation for participants. In this situation, users were asked to recall their emotions during the experiment and express their emotions in simple words. In the meantime, with the biological sensors, we could detect the bio-emotion during the emotion recalling. Lastly, we developed a system to compare the expressed emotion and the emotion detected using the biological sensors and gave feedback on the mismatched result to the user.

System design

Based on the bio-emotion estimation method, we used the EEG and heart rate sensors described above to develop our system. The design of the system is shown in Figure5.3. In this system, sensors will first collect biological information, that is EEG signals and heart rate. Secondly, the system will estimate emotion based on Ikeda et al.'s method[62], [63]. Third, the user will be asked to input his/her subjective emotion. Last, the system will compare the estimated emotion with the subjective emotion, and feedback the result of the comparison to the user.

In the system we designed, there are two functions: one is to estimate bio-emotion and the other is to compare emotions. In Fig. 4, we show the flowchart of the "bio-emotion estimation" function in (a) and the "emotion comparison" function in (b).

Based on the emotion estimation method proposed by Ikeda et al. [63], emotion estimate result is divided into four quadrants. After input measure

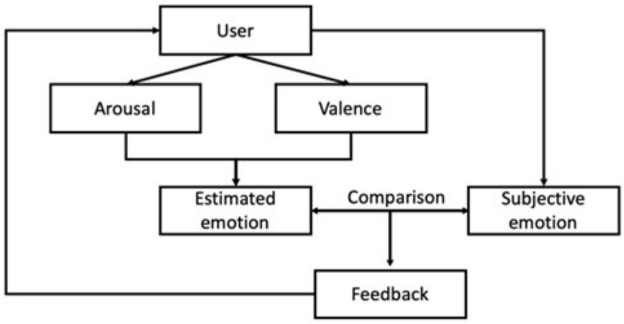

FIGURE 5.3: Bio-emotion feedback system

time, the measurement loop will start. The process is shown in Figure5.4 (a) runs every second until the measured time runs out. The final result of estimated emotion is determined by weight. Each quadrant stands for a basic emotion: the first quadrant stands for excitement, the second quadrant stands for distress, the third quadrant stands for sadness, the fourth quadrant stands for relaxation. The word of each quadrant is the word nearest to bisector on Russell's circumflex model.

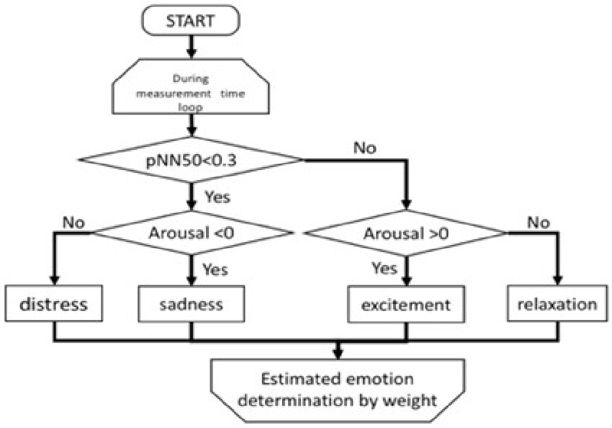

FIGURE 5.4: Bio-emotion estimation function in period time

After the measurement, the system runs the emotion comparison in Figure5.5. Since Russell's circumflex model has multiple emotion words at each quadrant, we put words in the same quadrant as a category, and the name of the category used basic emotion stands for each quadrant. The user will choose one word from all emotion words from Russell's circumflex model. Then the system will compare the category name of the word user chosen to estimated emotion. At last, the system will show the user the compared result as feedback.

After the measurement, the interface shows the user several emotion words, and the user can choose one word that describes their subjective emotion during the measurement time. After the chosen word is input, the system will give feedback on the comparison result to the user.

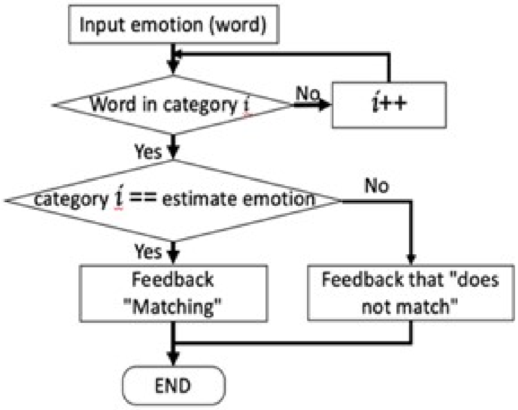

FIGURE 5.5: Comparison function between the estimated emotion and the subjective emotion

5.4.3 Experiment

Purpose

We had a preliminary experiment to evaluate the subjective opinion of our system in section 3.3 and find the significant result which shows the willingness of using the feedback system. As we introduced above, emotion feedback is normally used in e-learning and psychological therapy. In the case of e-learning, students' emotion is estimated and feedback to the teacher in order to help the teacher to adjust the teaching strategy. However, the feedback doesn't presented to the students themselves. On the other hand, during psychological therapy, the feedback is directly related to the change of physiological signals. Also, in order to take such therapies, it is necessary to attend the excise of using such system before the formal therapies. This makes the emotion feedback hasn't been applied to daily usage. The acceptance of such a bio-emotion feedback method is unknown to ordinary users. Therefore, we proposed to conduct subjective research on the bio-emotion feedback method. To verify the effectiveness of the proposed system, a comparative experiment was conducted. In the experiment, we hypothesized a situation for users. In this situation, users were asked to recall their emotions during the experiment and express their emotions in simple words. In the meantime, with the biological sensors, we could detect the bio-emotion during the emotion recalling. Lastly, we developed a system to compare the expressed emotion and the emotion detected using the biological sensors and gave feedback on the mismatched results to the user. However, it is necessary to figure out whether the emotion will change with the feedback system. Based on the Preliminary experiment's result, we designed this experiment to compare the bio-emotion changes between before feedback and after feedback

Experimental procedure

As the procedure of the experiment. Firstly, we asked the participant to wear the electroencephalogram sensor and the heart rate sensor. After the experiment starts, we ask participants to rest for one minute. And the recorded sensor value will be used as the baseline. Next in order to evoke the emotion of the participants we conducted a pre-questionnaire of their existing experience and the SAM of these existing experiences. During the experiment, the participants were asked to describe their experience with each emotion. the sensor will keep recording participants' EEG signal and the pNN50 signal. After the describing task, the participants were asked to input their emotion with the represent emotion word. The system compared the estimated emotion with the participants' declared emotion (participants' input) and feedback on the result to the participants. After the experiment, a questionnaire survey was carried out. In this experiment, there were 10 participants involved in the experiment. They are all male in their 20's and from Japan.

5.4.4 Result

To avoid the influence caused by the individual difference, we applies the Z-score to each bio-signals. First, we did a paired-sample t-test to compare difference of bio-signals under different stages. There was a significant difference between the rest stage and the after feedback stage when the evoked emotion is positive. The average of both bio-signals' Z-score is shown in Figure 5.6. The result of this experiment is shown in Figure.5.7: the blue box

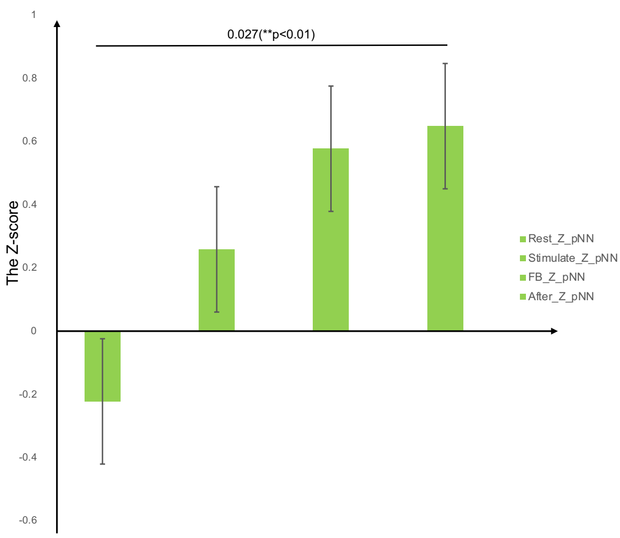

FIGURE 5.6: The average of EEG' Z-score and pNN50's Z-score while positive emotion state

is represented the z-score of the attention-meditation, and the orange box is represented the z-score of pNN50.

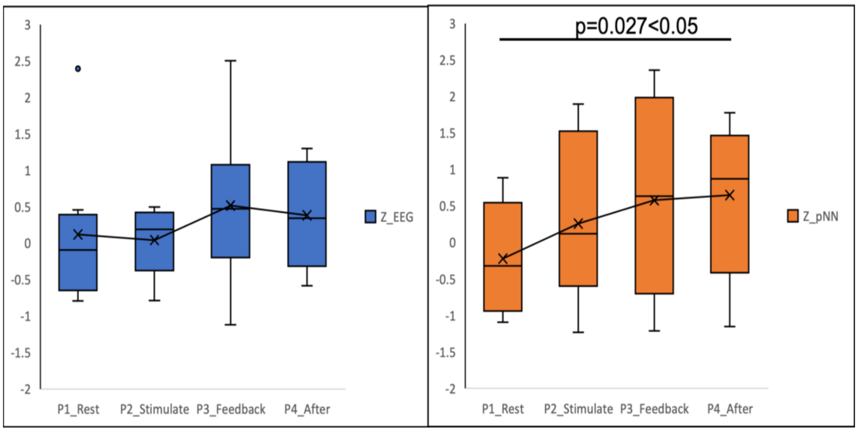

FIGURE 5.7: The boxplot of EEG' Z-score and pNN50's Z-score while positive emotion state

Figure5.7 The boxplot of EEG' Z-score and pNN50's Z-score while positive emotion state Figure5.7, shown the normalized EEG and pNN50 under positive emotion condition. The figure shows the significant difference(p<o.o5) on pNN50 between the rest stage and after the feedback stage.

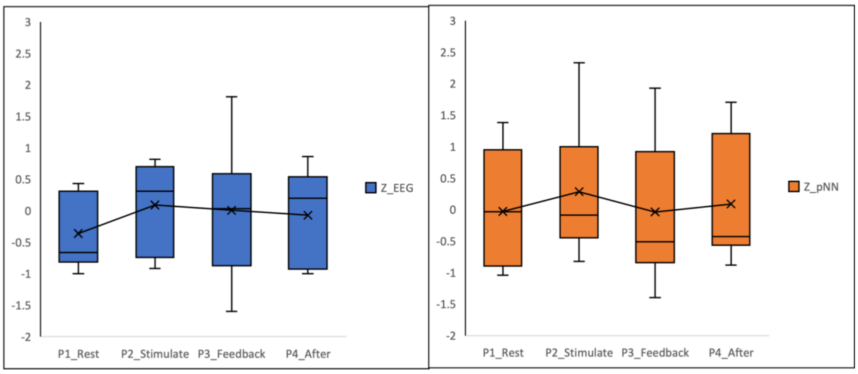

FIGURE 5.8: The boxplot of EEG's Z-score and pNN50's Z-score while neutral emotion state

Figure5.8 The boxplot of EEG's Z-score and pNN50's Z-score while positive emotion state The figure5.8, shows the normalized EEG and pNN50 under neutral emotion conditions. There is no significant difference was found in this condition. From the result shown above, we find out that participants want feedback for extra information to choose a more suitable expression. When we discuss the bio-signal divided, while the evoked emotion is negative, the pNN50, EEG; while the emotion is neutral, there is not much difference between before and after stage. Finally, while the emotion is positive, the signal does not change a lot either.

The figure5.9, shown the normalized EEG and pNN50 under negative emotion condition. There is no significant difference was found in this condition. Also, the result of the feedback changes the physiological signals, when the participants' subjective emotion matches the estimate result, the pNN50 increased, EEG index also increased. This study proposed to apply emotion estimation method to social media, in order to present bio-emotion to

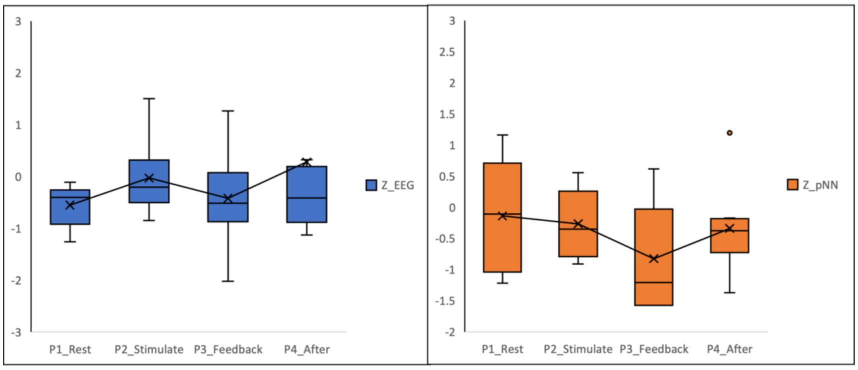

FIGURE 5.9: The boxplot of EEG' Z-score and pNN50's Z-score while negative emotion state

users before they present emotion with impropriate expression. This paper simply stimulates the situation users select emotional verb to express their emotion. Also, an experiment was occurred. Since this paper concentrate on the service development and evaluation of the innovative social media, we did not consider the accuracy of the emotion estimation method but depends on Ikeda et al.'s method which had shown the accuracy of emotion estimation method. However, this point is significantly important to evaluate the service. Therefore, it is necessary to consider accuracy when applying the feedback system to social media in practical usage and future works.

5.4.5 Discussion

During the experiment, even we show the effectiveness of our estimate emotion feedback system, there are still questions remind. Normally social networking servers are including instant messaging[28] and social networking sites[44]. The instant messaging such as "WhatsApp", "LINE" etc. provide instant communication from two users to a group of users. The importance of this type of service is the fluency of dialogs which usually happen in seconds. On the other side, social networking sites such as "Facebook", "LinkedIn", "Instagram" allow users to share their emotion expression any time [43]. However, when applying the emotion estimation method to both instant messaging and social networking sites, the emotion feedback method at this stage requires a period of time to estimate the user's biological information. And this causes a problem of the best time period to estimate emotion and a problem of the feedback timing. Participants mention different result makes them feel judged under period time bio-emotion feedback. As the next step, It is necessary to consider the accuracy of emotion estimation method; Also, since the timing of feedback cause unpleasant emotion, it is necessary to the best time period of emotion estimation. We also plan to include adverbs for the input words used in the present stage to the input content of the user in consideration of the discrimination strength. Such a study will identify and feedback the emotional strength. Emotion estimation based on biological information can be expected to have a wide range of applications in the future.

5.5 Bio-Emotion Feedback in real-time

5.5.1 Introduction

Based on the above experiments, we improved the system and recorded the physiological signal changes of the users before and after the feedback. In the positive emotion condition, we found significant differences between the resting phase and the post-feedback phase of pNN50. However, due to the short duration of the feedback cue, this finding does not provide sufficient evidence for an effective effect of feedback. Some participants explicitly expressed negative evaluations of the system. These negative comments focused on the impact of the feedback method. When the user's subjective state is not consistent with the presumed state, the user's negative feelings are deepened. At the same time, considering the usage scenario of social networks, which are usually fragmented, we consider changing the time period bio-emotion feedback to real-time emotional feedback. On this basis, since different users have opposite opinions about bio-emotion feedback, we consider that this is due to the different emotional traits of users.

Based on the research above, psychological research show that people exchange emotional expression in order to adapt to society and have social communication. These days, social communication evolves with Internet services. The computer-meditated social communication is widely speared, services such as WhatsApp, Facebook, Twitter, and so on, are provide. Such services are defined as social media. Through these social media, people exchange the emotion with selecting the phrases and characters as for expressing their emotions. These emotional expressions are selected generally based on the users subjective thinking, which sometimes can be unreliable. In this case, the expression could be inappropriate, or even convey a difference in subjective thinking and expression[99]. Such expression could cause the receiver to gain a mistaken impression. Such mistaken impressions might cause adverse effects on their relationships. We consider some helpful information for the user to give feedback on to avoid such situations

To achieve this goal, we first consider the possible causes of the users inappropriate expression. Muraven et al[28]. mention that human emotion subjectively affects expression, such as anger and sorrow. They also found that there is a tendency for human beings to have less control over themselves while they are experiencing vehement and negative emotions. Lin et al. concluded that mistakes occur when human beings do not recognize their own emotions at the time[31]. In these cases, such emotions would lead to inappropriate expression. Second, humans sometimes could accurately not recognize their own emotion, and what they expressed on social media are not what they truly feel[32].

On the other hand, an expression resulting from an bio-emotion is based on biological changes, which are affected by external stimulation. Humans themselves cannot manipulate such changes. Because of these two reasons, it is difficult for people to detect their bio-emotion themselves. To solve the problem, we consider some observable mechanisms that can detect the bio-emotions before users express their emotions on social media, which might be helpful for users in communication. In this research, we provide an observable mechanism to give feedback of bio-emotion to the users before they express emotion on social media. Since the bio-emotion is independent of the subjective expression of the user, the observable mechanism is dependent on the detection of the bio-emotion by biological sensors. Several research groups have discussed the detection of the bio-emotion using such sensors, such as brainwave and heart rate sensors[33], [34].

We applied the bio-emotion estimation method using biological sensors to the system. We also developed a function for comparing the bio-emotion with the expressed emotion and giving the user feedback of the results of comparison. For example, when experiencing anger or distress, the user might use inappropriate words or expressions before they recognize their own emotions. In this case, this system will detect the mismatch between the expressed emotion and bio-emotion, and feedback the result to the user. We designed and developed a system and conducted the experiment to show the effectiveness of the system in helping the user.

5.5.2 Real-time feedback system

System design

On the basis of the bio-emotion estimation method, we used the EEG and heart rate sensors described above to develop our system. The design of the system is shown in Figure5.10. In this system, sensors will first collect biological information, that is EEG signals and heart rate. Secondly, the system will estimate emotion based on Ikeda et al.'s method [62], [63]. Third, the user will be asked to input his/her subjective emotion. Last, the system will compare the estimated emotion with the subjective emotion, and feedback the result of the comparison to the user.

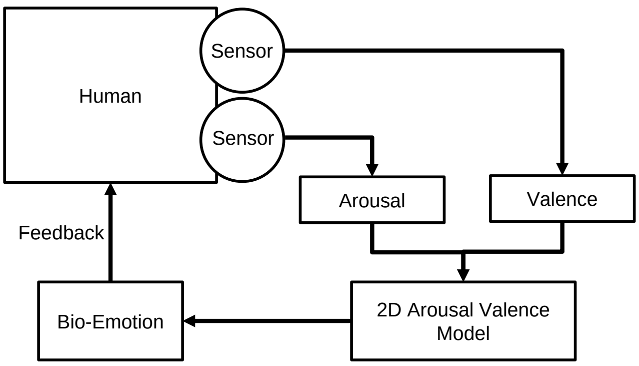

FIGURE 5.10: Bio-Emotion Feedback system

In the system we designed, there are two functions: one is to estimate bio-emotion and the other is to compare emotions. In Figure5.11, we show the flowchart of the "bio-emotion estimation" function and the Figure5.12 "emotion comparison" function in (b).

Based on the emotion estimation method proposed by Ikeda et al.[63], emotion estimate result is divided into four quadrants. After input measure time, the measurement loop will start. The process shown in Figure5.11 runs every second until the measure time runs out. The final result of estimate emotion is determinate by weight. Each quadrant stands for a basic emotion: the first quadrant stands for excitement, the second quadrant stands for distress, the third quadrant stands for sadness, the fourth quadrant stands for relaxation. The word of each quadrant is the word nearest to bisector on Russell's circumflex model.

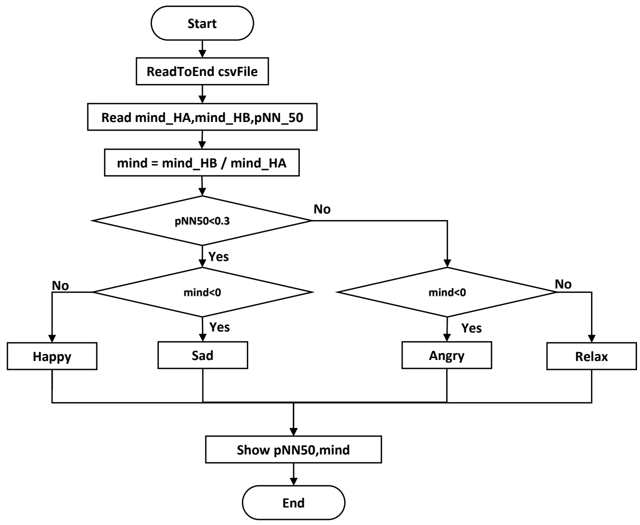

FIGURE 5.11: bio-emotion estimation

After the measurement, the system runs the emotion comparison in Figure5.12 Since Russells circumflex model has multi emotion words at each quadrant, we put words in the same quadrant as a category, and the name of category used basic emotion stands for each quadrant. The user will choose one word from all emotion words from Russells circumflex model. Then the system will compare the category name of word user chosen to estimated emotion. At last, the system will show the user the compare result as feedback.

The system interface is shown in Figure5.13 shows the interface of the system. The user was asked to press the start button the gray screen with a black cross will show in the display full screen size. After the end of rest time, the without feedback condition will start. In this condition, the interface will only show the instruction to ask the participant to do the reading task. And count down of this procedure will be shown on the top left on the window. After the countdown reach to zero, the gray screen will present again as a cool down time for participant. After the cool-down time, the screen will show the next instruction of reading task. In the meantime, the bio-emotion result will be shown on the window real-time. When the reading task is over, the system will present the gray screen with the black cross in the middle of the screen again until the rest time is over.

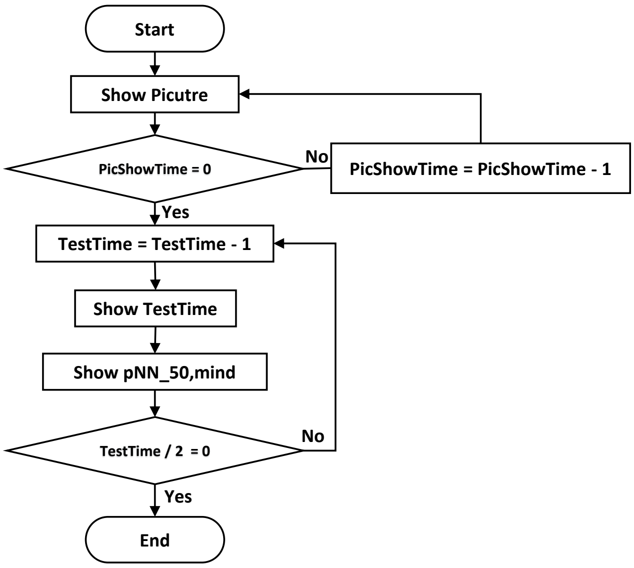

FIGURE 5.12: Bio-emotion feedback display function

(a) (b) (c)

FIGURE 5.13: The interface of the bio-emotion feedback(a)While the rest time condition, (b)While the without feedback condition, (c) While the with feedback condition

5.5.3 Experiment

Purpose

To verify the effectiveness of the proposed system, a comparative experiment was conducted. In the experiment, we hypothesized a situation for users. In this situation, users were asked to recall their emotions during the experiment and express their emotions in simple words. In the meantime, with the biological sensors, we could detect the bio-emotion during the emotion recalling. Lastly, we developed a system to compare the expressed emotion and the emotion detected using the biological sensors and gave feedback on mismatched result to the user. The effectiveness of the system was evaluated through the use of a questionnaire.

Experiment Procedure

The participants wear the electroencephalogram and the heart rate sensor at rest for 1 minute for baseline measurement. The participant was instructed to read one of the four scenarios from a prepared novel. To prompt the participants to recall their emotions, we asked the participants to recall their own similar experiences as they read one of the scenarios (from a novel). In the experiment, we asked users to express their emotions honestly to remove the influence of false expression. In the meantime, EEG and heartbeat sensors recorded the EEG signal and pNN50. After the measurement time the system estimated emotion using the 2-D arousal-valence model.

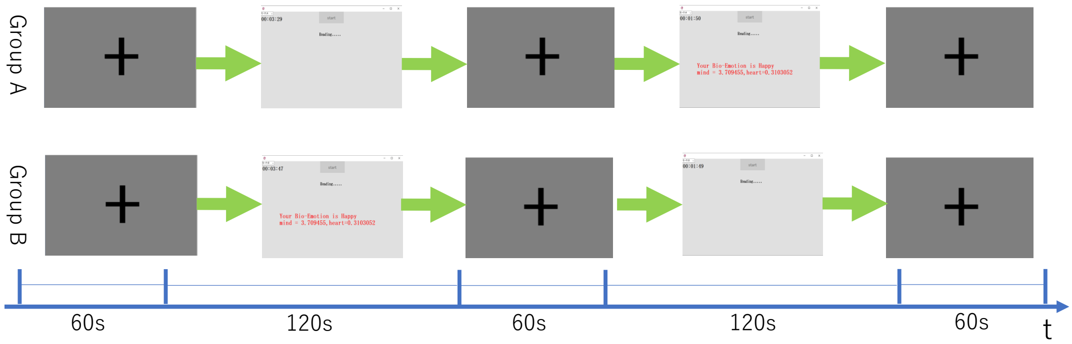

FIGURE 5.14: The Procedure of the Experiment

The system compared the estimated emotion with the participant's declared emotion (user's input). Finally, the system fed back the result to the participant. After the experiment, a questionnaire survey was carried out. In this experiment, there were 24 participants (9 males and 15 females) divided into two groups - the group with feedback and the group without feedback.

5.5.4 Subjective evaluation

During experiment of feedback in period time, we found out that different emotion intelligence cause the opposite reaction on the bio-emotion feedback. It is necessary to classify all participants by different emotion intelligence. Therefore we conduct a questionnaire to collect the trait emotion intelligence of participants. Also, to evaluate the participant's subjective opinions of the system, we conduct the user experiment questionnaire(UEQ).

Trait emotion intelligence questionnaire (TEIQue)

In order to solve the remain problems in the last experiment, we considered to classify the participants with their emotional intelligence. The TEIQue has been based on K. V. Petrides' theory of trait emotional intelligence[75]. Petrides' theory views emotional intelligence as a set of emotional self-awareness located at the lower levels of the personality hierarchy[100]. The trait EI provides a comprehensive assessment of an individual's emotional world. Among other psychological traits, the TEIQue specifically assesses our beliefs about our emotional competence (e.g., how good we believe we are at identifying, understanding, and managing our own and other people's emotions). The TEIQue includes 153 items translated into multiple languages. Since the TEIQue is a questionnaire can show the emotion factor of

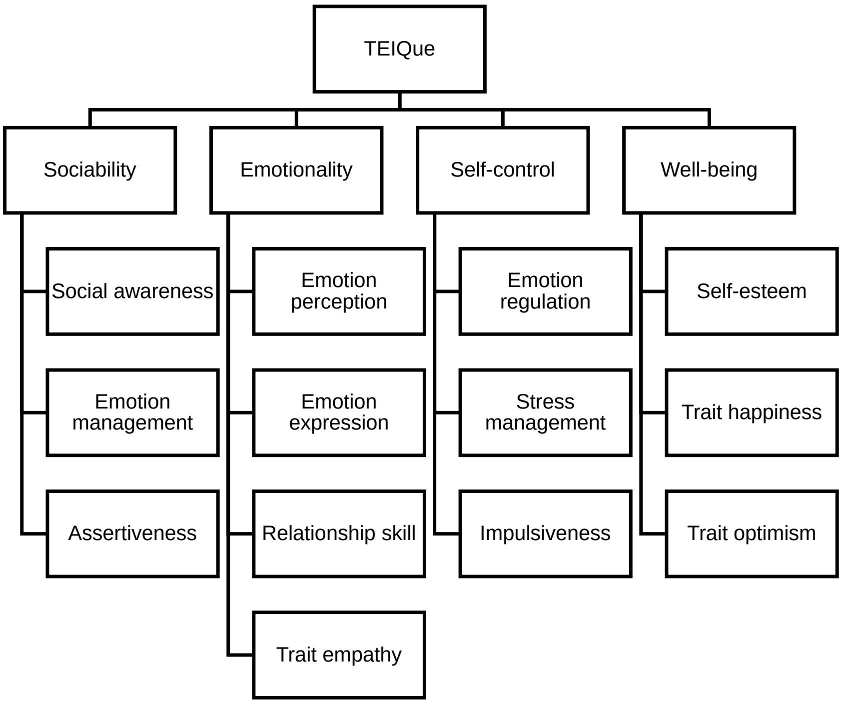

FIGURE 5.15: Four factors in TEIQue[75]

a person. Therefore, we used to divide the group of participants trait emotional intelligence. We had a preliminary experiment to evaluate the subjective opinion of our system and find the significant result which shows the willingness of using feedback system. However, it is necessary to figure out whether the emotion will change with the feedback system. Based on the Preliminary experiments result, we designed the main experiment to compare the bio-emotion changes between "before feedback" and "after feedback" . Therefore, we applied the TEIQue before the experiment.

User experience questionnaire (UEQ)

In order to evaluate our system, we conduct the user experiment questionnaire (UEQ) as the post questionnaire. The scales of the questionnaire cover a comprehensive impression of user experience. This questionnaire also includes multiple standard language version. Also, this questionnaire is easy to apply, reliable and valid measure for user experience that can be used to complement data from other evaluation methods with subjective quality ratings[101].

The Figure5.16 shows the distribution of the answers per each item. From the figure we can see that the item of cluttered-organized and the item inferior-valuable got a high evaluation. The item included in Figure5.16 is extract into six factors, which are the attractiveness, perspicuity, efficiency, dependability, stimulation, and the novelty. The average and the confidence interval are shown in Figure5.17. The range of the scales in between -3 (horribly bad) and +3 (extremely good).

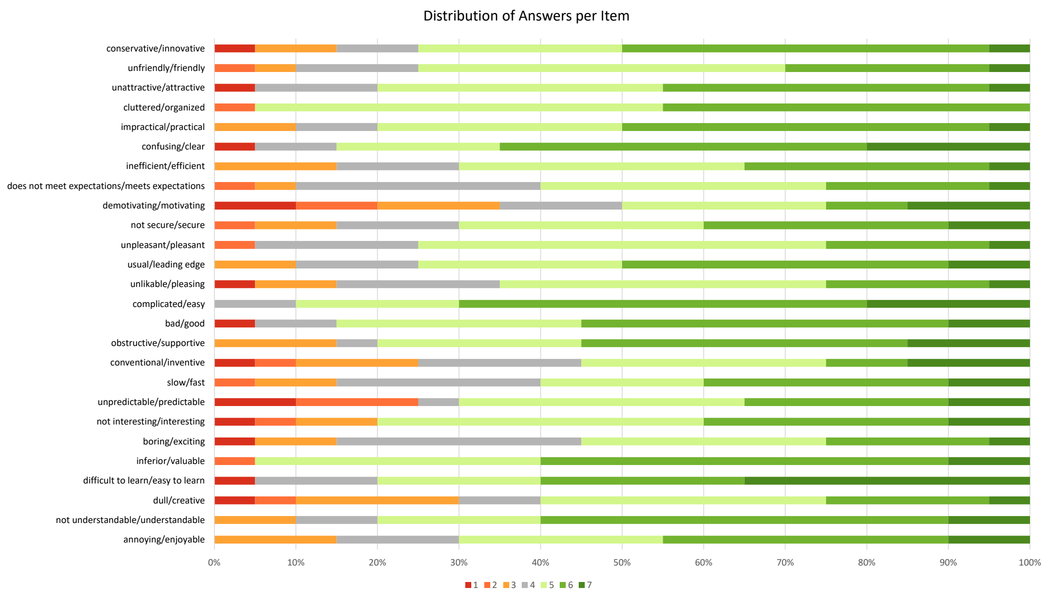

FIGURE 5.16: Distribution of answers per item in UEQ

5.5.5 Result

In this section we described our experiment result based on the analysis method. The table show the descriptive statistics result of Highβ / Highα As can be seen from the statistical description table, the mean level of the Without Feedback group was -1.476±0.5 and the mean level of the with feedback group was 1.526±0.54. After the descriptive statistics result, we did the Shapiro-Wilk normality test. The results of the normality test showed that the differences satisfied the normality test, therefore the paired-samples t-test be chosen in next step. The paired samples t-test showed that with feedback condition was lower than the mean of without feedback condition, with a difference of 0.05(-0.116 - 0.217) between the two groups, and the difference was not statistically significant ($t = 0.634$, $P > 0.05$). As the second value of EEG the statics result shown as below: The table show the descriptive statistics result of attention-meditation. As can be seen from the statistical description table, the mean level of the without feedback group was -6.473±11.024 and the mean level of the with feedback group was -8.028±13.158. After the descriptive statistics result, we did the Shapiro-Wilk normality test. The results of the normality test showed that the differences satisfied the normality test, therefore the paired-samples t-test be chosen in next step. The paired samples t-test showed that with feedback condition was lower than the mean of without feedback condition, with a difference of -1.555 (-8.446 -5.336) between the two groups, and the difference was not statistically significant ($t = -0.472$, $p > 0.05$) Next is the statical result of pNN50 as below: The table show the descriptive statistics result of attention-meditation. As can be seen from the statistical description table, the mean level of the Without Feedback group was 0.209±0.14 and the mean level of the with feedback group was 0.238±0.15. After the descriptive statistics result, we did the Shapiro-Wilk normality test. The results of the normality test showed that the differences

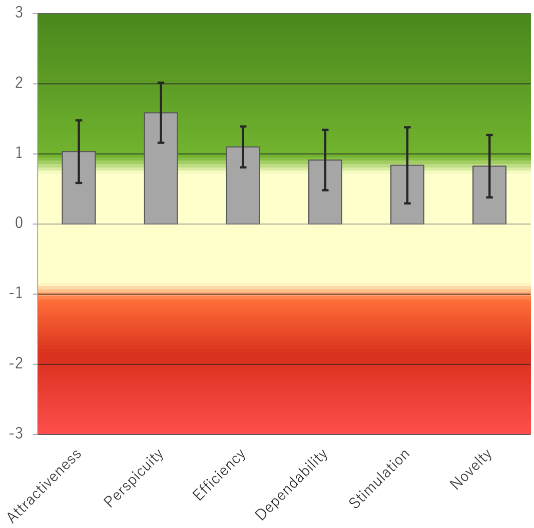

FIGURE 5.17: The average and confidence of the six factor in six scales

satisfied the normality test, therefore the paired-samples t-test be chosen in next step. The paired samples t-test showed that with feedback condition was higher than the mean of without feedback condition, with a difference of 0.029 (-0.01 - 0.067) between the two groups, and the difference was not statistically significant ($t = 1.567$, $P > 0.05$) Based on the result above we used the Z-score to normalize the data and the box plot of all participants is shown as below:

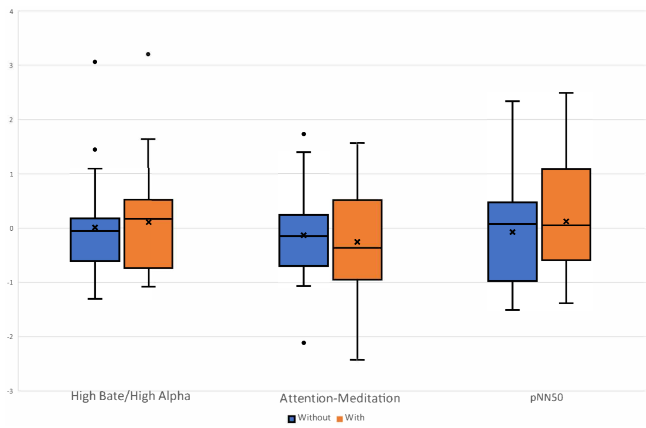

FIGURE 5.18: The box-plot of all participants in Z-score

After shown the average of all participants, based on the TEIQue in the 5.5.3, we divide 20 participants into two group by four different TEIQue factors. The factors include sociability, self-control, well-being, and emotionality. Basing on the questionnaire, each participant has four score to the four factors. Belong to each factor, we rank the score of each participant so the participant could be dividing into top ten and last ten. The top ten participants will belong to the high group, and the last ten participants belongs to the low group. Based on the grouped result, we did the paired t-test.

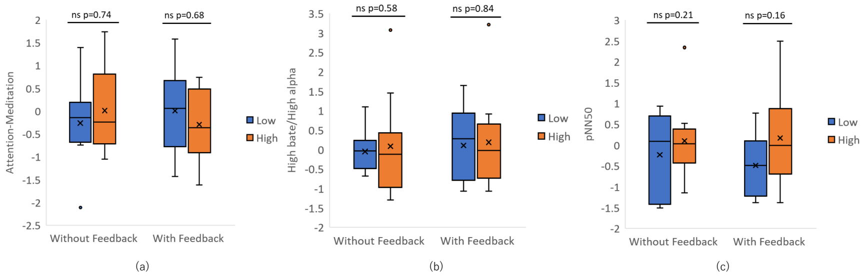

FIGURE 5.19: The box-plot of Sociability (a)Attention-meditation(b)High β/High α(c)pNN50

The Figure5.19 shows the result of grouping by sociability. The (a) show the EEG index attention-meditation. From the figure we can see that the attention-meditation value increase in the low sociability group and decrease in the high sociability group. Also, the high beta/ high alpha. In the group with low sociability, although the average did not raise to a high level, most of the participants' valence(pNN50) is increased from below average to above average. This shows that the feedback of bio-emotion helps participants regulate the emotion state from tense state to relax state.

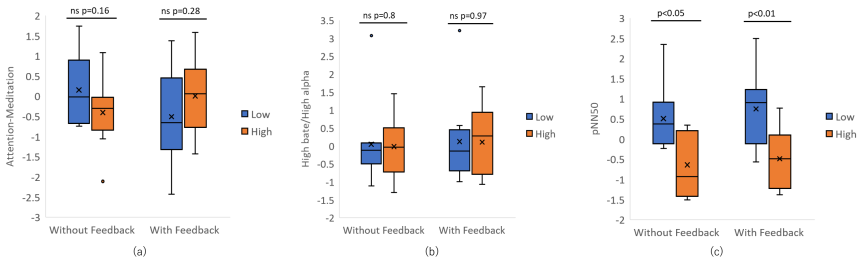

FIGURE 5.20: The box-plot of Self-Control (a)Attention-meditation(b)Highβ/High α(c)pNN50

The Figure5.20 shows the result of grouping by self-control. S although the average did not raise to a high level, most of the participants' valence(pNN50) is increased from below average to above average.

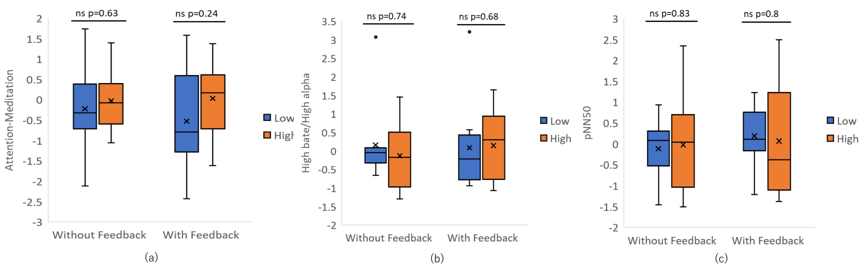

FIGURE 5.21: The box-plot of Well-being (a)Attention-meditation(b) High β/High α(c)pNN50

The Figure5.21 shows the result of grouping by well-being, although the average did not raise to a high level, most of the participants' valence(pNN50) is increased from below average to above average.

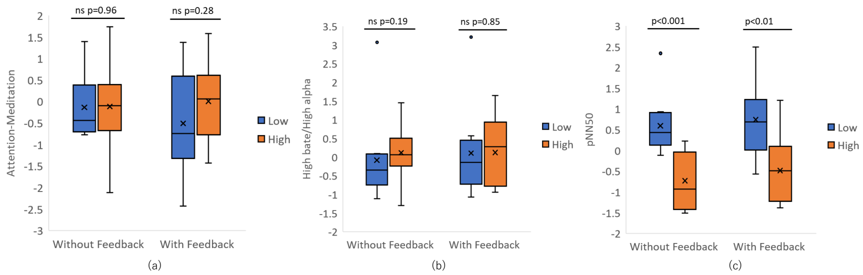

FIGURE 5.22: The boxplot of Emotionality (a)Attention-meditation(b) High β/High α(c) pNN50

The Figure5.22 shows the result of grouping by emotionality. In the group with low well-being, although the average did not raise to a high level, most of the participants' valence(pNN50) is increased from below average to above average. This shows that the feedback of bio-emotion helps participants regulate the emotion state from tense state to relax state. The index related to EEG didn't get a significant result could also cause by the reading task makes the participants felt boring during the experiment.

Based on the grouped result of we took a further step to the case analysis. And the result is shown as below.

Participants A4: participants A4 is female at 20's. She reported that she didn't regulate emotion state on purpose while noticing the present of bio-emotion feedback while using social media.

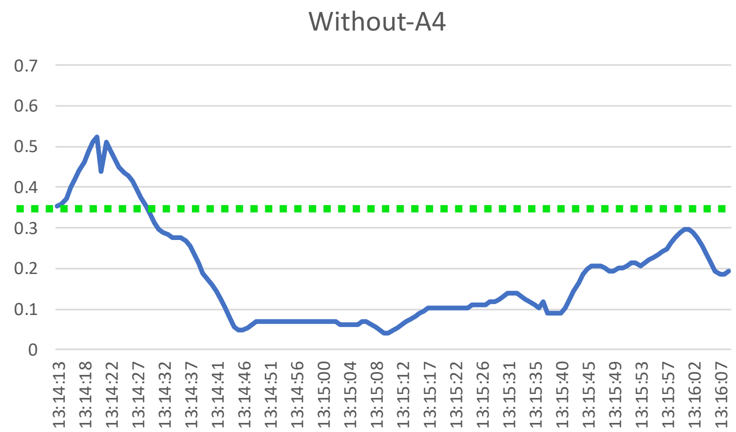

FIGURE 5.23: The pNN50 of participants A4 under without feedback condition

The Figure5.23 shows her pNN50 under the without feedback condition. In this condition, pNN50 remain decreasing until a low level and remain low level for a while.

The Figure5.24 shows her pNN50 under the with feedback condition. Even the participants report that she noticed the feedback of bio-emotion but didn't regulate her emotion state consciously. From Figure5.24 we can also find out during the decease of pNN50, the pNN50 still has lightly rise for serval times. We can tell that in participants A4's situation, the feedback of bio-emotion helped the participant to regulate her emotion state in unconsciously. However, the limitation of this result is still existed. In this experiment, we haven't measured the specific timing and how many times of when did participant A4 are noticing the feedback.

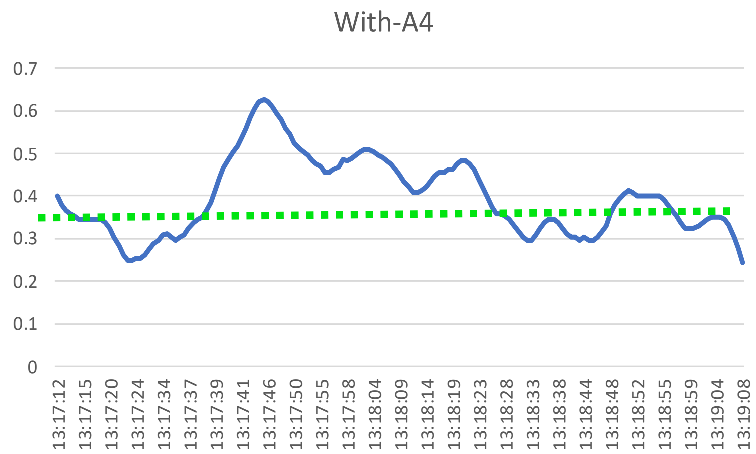

FIGURE 5.24: The pNN50 of participants A4 under with feedback condition

Participants B5: participants B5 is also female at 20's. The Figure5.25 shows the pNN50 change under without feedback condition. Although participants B5 reported that the negative content on social media didn't evoke her strong and negative emotions. From Figure5.25, we still found a decrease of pNN50, after a short time of decreasing, the pNN50 return to almost the same level as start. Also, from the questionnaire, participants B5 reported she has a high level of self-control. Combine with the questionnaire, the result suggests that participants regulated her emotion without the aware the emotional state changes.

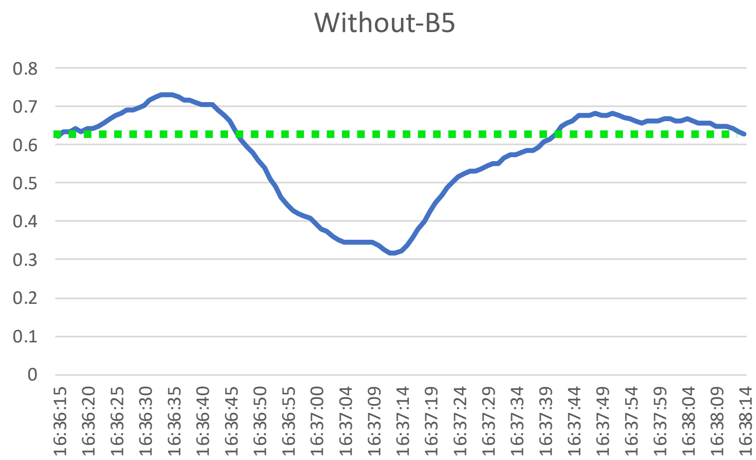

FIGURE 5.25: The pNN50 of participants B5 under without feedback condition

The Figure5.26 shows the change of pNN50 under with feedback condition. The pNN50 didn't decrease obviously. According to the interview after the experiment, participant B5 mentioned that she noticed the feedback of bio-emotion while reading the negative contents on social media. However, she didn't attempt to regulate her emotion state consciously. This result also suggests the point we mentioned in participant A4's situation which is the feedback of bio-emotion could regulate emotion state unconsciously.

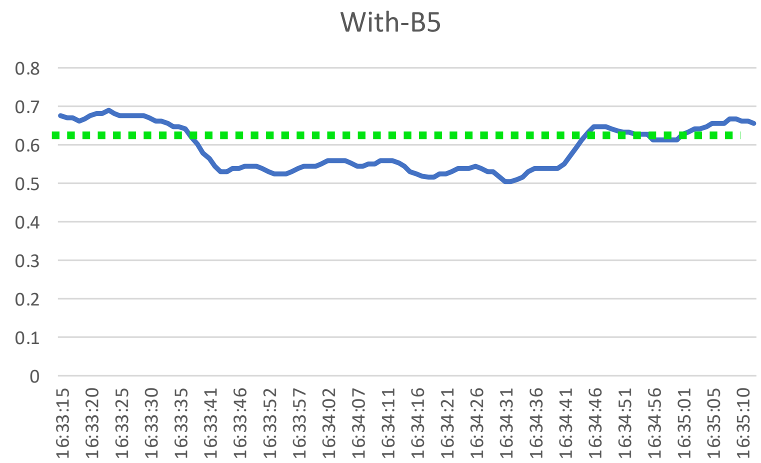

FIGURE 5.26: The pNN50 of participants B5 under with feedback condition

5.5.6 Discussion

From the result shown above, we find out that participants want feedback for extra information to choose a more suitable expression. When we discuss the bio-signal dividedly, while the emotion is negative, the pNN50, EEG; while the emotion is neutral, there is not much difference between before and after. Finally, while the emotion is positive, the signal does not change a lot either. Also, the result of the feedback changes the physiological signals, when the participants' subjective emotion matches the estimated result, the pNN50 raise, EEG index raise.

According to the emotional intelligent trait questionnaire result, we divide participants into the high group and the low group in each factor. In the group with low sociability, although the average did not rise to a high level, most of the participants' valence(pNN50) is increased from below average to above average. This shows that the feedback of bio-emotion helps participants regulate the emotion state from tense state to relax state. Also, in both with and without feedback conditions, there is a significant difference (without feedback: $p<0.05$, with feedback $p<0.01$) between the high self-control group and the low self-control group. The pNN50 level does not change by bio-emotion feedback. We found out that both with and without group the low self-control group is higher more relaxed (higher pNN50 value) than high self-control group. And for the well-being trait, even there is no significant difference, the feedback of bio-emotion helps participants regulate the emotion state from tense state to relax state. For the trait of emotionality, in both with and without feedback conditions, there is a significant difference (without feedback: $p<0.05$, with feedback $p<0.01$) between the high emotionality group and the low emotionality group. The pNN50 level does not change by bio-emotion feedback. Since the pNN50 is shown the difference of tense and relaxed emotion state of participants, we selected the participants with self-report to conduct case analysis.

In the case analysis part, Participants A4: participants A4 is female in 20's. She reported that she didn't regulate emotion state on purpose while noticing the presence of bio-emotion feedback while using social media. The Figure 5.23shows her pNN50 under the without feedback condition. In this condition, pNN50 remains to decrease until a low level and remain low level for a while. The Figure5.24 shows her pNN50 under the with feedback condition. Even the participants report that she noticed the feedback of bio-emotion but didn't regulate her emotion state consciously. From Figure5.24 we can also find out during the decrease of pNN50, the pNN50 still has lightly rise for serval times. We can tell that in participant A4's situation, the feedback of bio-emotion helped the participant to regulate her emotion state unconsciously. However, the limitation of this result still exists. In this experiment, we haven't measured the specific timing and how many times of when did participant A4 are noticing the feedback.

Participants B5: participants B5 is also female at 20's. The Figure5.25 shows the pNN50 change without feedback condition. Although participant B5 reported that the negative content on social media didn't evoke her strong and negative emotions. From Figure5.25, we still found a decrease of pNN50, after a short time of decreasing, the pNN50 returned to almost the same level as the start. Also, from the questionnaire, participant B5 reported she has a high level of self-control. Combine with the questionnaire, the result suggests that participants regulated her emotion without the aware of the emotional state changes. The Figure5.26 shows the change of pNN50 under with feedback condition. The pNN50 didn't decrease obviously. According to the interview after the experiment, participant B5 mentioned that she noticed the feedback of bio-emotion while reading the negative contents on social media. However, she didn't attempt to regulate her emotion state consciously. This result also suggests the point we mentioned in participant A4's situation which is the feedback of bio-emotion could regulate emotion state unconsciously.

Chapter 6

Conclusion

6.1 The Evaluation of Bio-Emotion Estimation

To evaluate this method, it is important to evoke a specific emotion. In the meantime, the previous research shows that aroma is wildly applied to therapies since aroma can effect emotion. Therefore, we use aroma as the emotion-evoking material and conduct an experiment. The experiment is aiming to evaluate the effectiveness of the bio-emotion estimation method by comparing the bio-emotion estimation result and the self-assessment manikin (SAM) result of the participants. As the result of the experiment, we found that among four of five types of aromas, the bio-emotion estimation result matches the SAM result. Except for one negative aroma which caused a huge raising in heart rate. In this case, the bio-emotion estimation method gained an opposite result from the SAM result. This experiment demonstrated the valence of Ikeda's bio-emotion estimate method in normal emotion-evoking situations.

6.2 Biofeedback with Emotion

6.2.1 Subjective evaluation of bio-Emotion feedback

Basing on the idea we proposed to applied bio-emotion estimation method with the biofeedback to help user notice their own emotion. However, it is the first time bio-emotion is directly applied to the biofeedback. Therefore we conduct a experiment, to let the participants to experience our prototype system. The first experiment is to evaluate the effectiveness of the bio-emotion estimation method. Also, the result shows us that, based on the result of the questionnaire we find out that, after using the bio-emotion feedback system, the user has more preference of getting suggestions before expression. The significant difference shows bio-emotion feedback system could be accepted by the users. According to the participants' interview, we found that as the emotion-evoking, the selection of novel clips is subjective and sometimes couldn't evoke participants' emotion. On the opposite, the participant who had a similar experience with the novel clip reported that their emotion is evoked easily while reading the novel clip.

6.2.2 Bio-emotion feedback in period time

Based on the result of the preliminary experiment of bio-emotion feedback, we improved this system and compared the physiological signal changes of the users before and after the feedback. As the result of this study, under the positive emotion condition, we found significant differences between the rest procedure and the post-feedback procedure on pNN50. However, due to the short duration of the feedback, this result might cause by the positive emotion maintaining. When the user's subjective emotion state is not consistent with the estimated emotion state, the user's negative emotion is deepened. We consider that this is due to the different emotional traits of users. Since different emotional traits could cause. At the same time, considering the usage scenario of social networks, which are usually fragmented, we consider changing the time period bio-emotion feedback to real-time emotional feedback. On this basis, since different users have opposite opinions about bio-emotion feedback, we consider that this is due to the different emotional traits of users.

6.2.3 Bio-emotion feedback in real-time

In summary, real-time bio-emotion feedback can have an impact on users' emotional states. The application of bio-emotion feedback in social media can be expected. Meanwhile, in this study, we still set up the biosensor conditions under laboratory conditions. Therefore, in the future, we consider introducing a commercial wearable device to provide feedback on specific negative affective states of users during social media usage. At the same time, since affective feedback allows users to unconsciously mediate their affective states, we expect that bio-emotion feedback can also be applied to mediate users' affective states and maintain mental health.

6.3 Future Work

This bio-data analysis has not been fully verified yet. In the future, we would like to verify the difference between the user's subjectivity and the measurement results by adding the physiological data analysis. Furthermore, the emotion comparison function that we are currently using is designed mainly as a database search function. In the future, we would like to use natural language processing as a means of comparing emotions and realize more freedom in user expression. We need to consider the questions mentioned above: 1. the accuracy of the emotion estimate method; 2. the best time of emotion estimate; 3. an effective feedback timing. We also plan to include adverbs for the input words used in the present stage to the input content of the user in consideration of the discrimination strength. Such a study will identify and feedback the emotional strength. Emotion estimation based on biological information can be expected to have a wide range of applications in the future.

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