An Analysis of Correlations between Empathy and Both EEG and HEG during Text Chat

Masaki Omata¹ and Kana Watanabe²

¹Graduate Faculty of Interdisciplinary Research, University of Yamanashi, Kofu, Yamanashi, Japan ²Department of Computer Science and Engineering, University of Yamanashi, Kofu, Yamanashi, Japan

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Abstract: We have addressed a problem that emotions associated with texts are not correctly conveyed in text chat. In this study, we conducted two experiments to analyze whether electroencephalography (EEG) and hemoencephalography (HEG) of a receiver can be used to identify the receiver's empathic state when the receiver is empathizing with the emotion associated with the text sent by a sender. As the results, we found that emotional valence was more likely to be empathized with in text-based chat, but emotional arousal was less likely to be empathized with. We also found that the power of theta waves at O1 (in the occipital region) of the empathic receivers was significantly lower than that of the non-empathic receivers.

1 INTRODUCTION

People communicate using a variety of modalities such as text, voice, and video with increasing popularity of smartphones and social networking services (IICP of MIC, 2019). Among the modalities, text-based communication, such as chat and email, has an advantage of being less constrained in time and space, and is easier to communicate anytime and anywhere. On the other hand, a disadvantage of textbased communication is that it lacks visual information (such as facial expressions and body language) and auditory information (such as tone and volume of voice) compared to voice, video, and faceto-face communication, and thus may not correctly convey emotions to a receiver. If the emotions are not conveyed correctly to the receiver, there is a possibility that the receiver will not understand the emotions and will not sympathize with them.

To address the problem, we have proposed use of physiological signals of the receiver to estimate the receiver's empathy with regard to emotions of conversational content in the text. The reason for using physiological signals is that physiological signals can be measured continuously and unconsciously, and can be used without burdening users with interruptions or interventions during a text conversation. If our proposed system is able to estimate empathy from physiological signals, it will be able to feed back the receiver's empathy to the sender immediately during text chatting, which will make communication smoother in the future.

In this paper, we introduce related studies and indicate the position of our study in the next section. After that, we explain the first experiment, which examines correlations between the empathizer's emotions and both electroencephalography (EEG) (Nunez et al., 2007) and hemoencephalography (HEG) (Tinius, 2004) during text chatting. Then, we explain the second experiment, in which we added data based on the results of the first experiment. Our contribution in this paper is that we mentioned the possibility of using the theta waves of the EEG on the occipital region of the empathizers (receivers) to estimate their empathies generated from the text chat.

2 RELATED WORK

Kinoshita et al. measured affective sharing from EEG signals and conducted an experiment in which participants communicated using facial expressions of joy, sadness, and neutrality (Kinoshita et al., 2019). The results showed that correlations of EEG powers were significantly higher under the high affective sharing condition compared to the low affective sharing condition, and that the correlations of the EEG powers were significantly higher under the joy

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and sadness conditions in the alpha-mu band. The results have suggested possibility to measure affective sharing in response to emotional faces from the correlation of EEG powers.

Vanderhaegen et al. studied synchronization between dynamic events with heartbeats on nonconscious errors in the control of dynamic events by comparing two groups of subjects: a group for which alarms were activated synchronously with the current heart rate of the subjects and a group for which the alarms were activated without being synchronized with the current heart rates of the subjects (Vanderhaegen et al., 2020). The results showed that there was a significant impact of such a synchronization of events with heartbeat.

Jain et al. looked at and analyzed how messages sent on instant messages or posts on social networks are interpreted by readers in terms of the emotional state of the sender (Jain et al., 2016). As the results of Spearman's rank-correlation coefficient about the Self-Assessment Manikin (SAM) (Bradley et al., 1994), they found that a high correlation ($\rho = 0.80$) was found between valence of the sender for each message and perceived valence of the sender, and that no correlation ($\rho = 0.11$) was found between arousal of the sender for each message and perceived arousal of the sender. These indicated how easily and accurately valence is conveyed while arousal is almost never conveyed accurately.

Ghosh et al. designed and implemented an Android application TapSense which traced smartphone typing and records self-reported emotion state and conducted an online survey to understand the typing habits in smartphones and collect feedback on multiple measurable parameters that affect their emotion while typing (Ghosh et al., 2017). As the results, they observed that using only typing features, it was possible to identify four emotion states (happy, sad, stressed and relaxed) with an average accuracy of 73% and a maximum of 94%.

We believe that if it is found that physiological signals can be used to estimate the receiver's empathy as in Kinoshita et al. (Kinoshita et al., 2019) in text chatting, which is our research target, we will be able to provide a user interface that supports smoother communication with emotions in text chatting than before. Specifically, we have been designing a user interface that sequentially estimates the receiver's empathy from the physiological signals and provides feedback to the sender on a receiver's level of the empathy, and a user interface that automatically decorates text according to the receiver's level of empathy. The reason for using physiological signals in this way is that physiological signals are not as subjectively controllable by the user intentionally as questionnaire surveys, can be measured continuously, and do not interfere with the user's operation. For this purpose, in this paper, we asked senders and receivers to answer their emotions in text chat using SAM, as in Jain et al. and then recorded the receivers' EEG and HEG, as in Kinoshita et al. (Kinoshita et al., 2019) and analyzed the correlation between the receivers' emotions and the physiological signals.

3 EXPERIMENT FOR ANALYSIS OF PHYSIOLOGICAL SIGNALS DURING EMPATHY

In this experiment, we analyzed correlation between physiological signals and empathy for chat text by recording physiological signals of receivers during text chat and comparing them with their normal conditions.

3.1 Physiological Signals

Electroencephalography (EEG) and hemoencephalography (HEG) were measured in this experiment. The EEG and HEG sensors were connected to an encoder (Thought Technology Ltd., ProComp INFINITI) (Thought Technology Ltd., 2022). In this section, the properties of the physiological signals are described.

3.1.1 EEG

EEG is a record of the oscillations of brain electric potentials recorded from electrodes attached to the human scalp (Nunez et al., 2007). The frequency ranges are categorized as delta (0.5 to 3 Hz), theta (4 to 7 Hz), alpha (8 to 13 Hz) and beta (14 to 30 Hz). Very high frequencies (typically over 40 Hz) are referred to as gamma activity. In general, theta waves are seen in deep meditation and slumber, alpha waves are seen in relaxation, and beta waves are used as the physiological indexes of this experiment. The BioGraph INFINITI and BioGraph Infiniti Software Platform of Thought Technology Ltd. were used to calculate the power values.



Figure 1: The EEG sensor and its installation.



Figure 2: The HEG sensor and its installation.

The EEG-Z sensor from Thought Technology, shown in Figure 1, was used as the electrodes for the EEG measurement. Three probe electrodes were placed at Fp1 (left front polar), O1 (left occipital) and O2 (right occipital) according to the International 10– 20 system (American Electroencephalographic Society Guidelines for Standard Electrode Position Nomenclature, 1991).

3.1.2 HEG

A HEG is relative ratio of oxidized hemoglobin to deoxygenated hemoglobin with blood flow dynamics and cellular metabolism in localized parts of the brain cortex (Tinius, 2004). The measurements are closely linked with brain activation due to the phenomenon of neurovascular coupling. The HEG ratio (Serra-Sala et al., 2012 and Skalski et al., 2021), calculated from the increase or decrease of oxidized hemoglobin and deoxidized hemoglobin in the blood flow to the location of the frontal cortex, was used as a physiological index in our study.

We used MediTechElectronic's HEG-Sensor shown in Figure 2 in order to measure the ratio. The measurement point was Fp2 (right forehead) of the International 10–20 system.

3.1.3 Standardization

We standardize the recorded physiological indexes by referring to the method of Omata et al (Omata et al., 2014) to analyze the variation of the indexes during an experimental task from the indexes in resting state. EEG and HEG-ratio are standardized as shown in Equation (1),

$$Z = \frac{X - \mu}{\sigma} \tag{1}$$

where X is the data of each physiological index during the experiment, μ is the mean value of the normal state, and σ is the standard deviation.

3.2 Environment and Participants' Roles



Figure 3: An emotional generator (a) and an empathizer (b) during the experiment task.

As shown in Figures 3a and b, two of the participants chatted using laptop computers in two rooms separated by a barrier that prevented them from directly seeing and hearing each other. We chose slack (Slack Technologies, 2022) as the chat system for this experiment because it is intuitive and easy to understand for the participants, and because it is easy for the participants to reproduce emotional expressions more richly by using pictorial reactions (Slack Technologies, 2022).

The two participants were asked to chat with each other mainly using text, and each was assigned a role for this experiment. One of the two was assigned the role of transmitting emotional experiences through the chat (hereinafter called the "emotion generator"), and the other was assigned the role of empathizing with the received emotional experiences (hereinafter called the "empathizer"). The empathizer was equipped with the physiological signal sensors as described above.

3.3 Procedure and Task

We asked the participants to participate in the chat experiment in pairs (emotion generator and empathizer). First, we gave informed consent to these two participants and obtained their consent to participate in the experiment. After that, we took them to separate rooms, sat them in front of a laptop computer for chatting, and explained how to use slack.

Before chatting, the emotion generator was asked to recall his/her own happy and sad experiences, and to rate the experiences on 9-point scale of emotion valence and 9-point scale of arousal of the Self-Assessment Manikin (SAM) (Bradley et al., 1994). On the other hand, the empathizer was equipped with physiological signal sensors. Then, the physiological signals were recorded for one minute while the sympathizer was resting and doing nothing, to be used as baseline data for analyses.

The experimental task for both the participants was to have a chat conversation about the happy and sad events that the emotion generator remembered. Before starting the chat, both the participants were asked to familiarize themselves with slack for two minutes (or more if either of the two requested it). At the start of the chat task, via the chat system, the experimenter instructed the emotion generator "Please tell the other participant about the experience you recalled and try to convey the emotion of the experience as much as possible," and instructed to the empathizer "Please be a collocutor of the other participant's story and try to capture the emotion of the story." After the experimenter signaled the start of the chat, both the participants chatted for about three to five minutes based on the instructions. During the chat, the physiological signals of the empathizer were continuously recorded. The experimenter read the content of the chat, and signaled the end of the chat when the conversation was finished. Then, the physiological signals of the empathizer were recorded again for one minute while she was at rest doing nothing.

After the chat was over, the empathizer was asked to answer the emotion she recognized from the chat text and the emotion she felt as a result of the conversation by using the SAM. After a five-minute break, the participants performed the same task for the other experience that the emotion generator recalled. The number of pairs that started with happy experiences was equal to the number of pairs that started with sad experiences in order to counterbalance the order of happy and sad experiences in the chat contents.

After completing the chat task for the two emotions, both the participants were asked to complete a questionnaire survey about their past experience in using slack and their impressions of using slack to express the emotions in this experiment.

Eight participants (one male and seven females, ranging in age from 21 to 23 years) participated in this experiment. All of them had experience using slack before the experiment. When creating pair combinations from the participants, we paired them with the pairs that they usually communicate with via text chat. The empathizers in each pair were all female. The reason for this was based on the results of Davis's study that women were more likely to empathize than men (Davis, 1980).

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3.4 Results

3.4.1 Correlation Analysis of Subjective Emotions

Figure 4 shows the relationship between the emotional valence (from negative (1) to positive (9)), that the emotion generators responded about the experiments they recalled and the emotional valence (from negative (1) to positive (9)) that the empathizers felt from the chat. Since the participants were asked to chat about happy and sad events, the plot points were divided into two groups. The Spearman correlation coefficient for the plots is 0.948. This indicates that both emotion generators and empathizers had similar emotional valences.

Figure 5 shows the relationship between the arousal (from low (1) to high (9)) that the emotion generators responded about the events they recalled and the arousal (from low (1) to high (9)) that the empathizers felt from the chat. Since the Spearman correlation coefficient for the plots is 0.621, there was no correlation like that of the emotion valence, and there

were differences in the arousal levels held by emotion generators and empathizers.



Figure 4: The relationship between the emotional valence (from negative (1) to positive (9)) of the emotion generators and the emotional valence (from negative (1) to positive (9)) felt by the empathizers from the text chat.



Figure 5: The relationship between the emotional arousal (from low (1) to high (9)) of the emotion generators and the emotional arousal (from low (1) to high (9)) felt by the empathizers from the text.

3.4.2 Correlation Analysis between Physiological Signals and Subjective Emotions

The power values of the three frequency bands (alpha, beta, and theta) in the EEG at three locations (Fp1, O1, and O2) and the HEG ratio at one location (Fp2) were analyzed for significant differences among the three states: resting state before the task, happy empathy, and sad empathy. As the results, there was a significant difference (p < .05) between the resting state and the happy empathy state in the power values

of theta waves measured at O1 and O2. There was no significant difference (p < .05) in the HEG ratio.

Figures 6 and 7 show the correlations between the power values of theta waves at O1 and O2 and the subjective emotional valence of the empathizers during resting and happy empathy, respectively. Here, the empathizer's valence at rest is set to 5, which represents a neutral emotional state. Therefore,



Figure 6: Relationship between the emotional valence of the empathizers and the power value of the theta waves of O1.



Figure 7: Relationship between the emotional valence of the empathizers and the power value of the theta waves of O2.

these graphs show that the power value of the theta waves increases when the neutral emotional valence at rest is positively changed by empathy for happiness. The R^2 in each of the graphs is its coefficient of determination.

3.5 Discussions

Based on the results of SAM, we found that emotional valence is easily conveyed but arousal is not easily conveyed in text-based chat. This is consistent with the results of the study by Jain et al (Jain et al., 2016). From the analysis of physiological signals, we found

that the power value of the theta wave band of the occipital EEG increased during empathy for chatting about happy events. This result is in line with the results of Knyazev's study that theta waves are related to emotion regulation (Knyazev, 2007). Therefore, we argue that occipital theta waves can be used to estimate a state of positive empathy of chat users toward the chat contents.

4 FURTHER EXPERIMENT

We conducted another experiment to add more participants' data to the aforementioned experiment. The environment, the roles of participants, the procedure, and the task were the same as in the aforementioned experiment. However, this experiment differs from the previous one in the following points.

- The results of SAM in the aforementioned experiment suggest that some participants remembered "Angry" and "Afraid" in Russell's circle model (Russell, 1980). However, we wanted them to remember Sad, so we instructed participants to recall a sad experience, not a bad experience.
- We asked participants to recall the recent experiments in order to generate the arousal level more accurately.
- Men were included in empathizers.

4.1 Results

4.1.1 Correlation Analysis of Subjective Emotions

Figure 8 and 9 show the relationship between the emotional valence (from low (1) to high (9)) and arousal (from low (1) to high (9)) that the emotion generators responded about the experiments they recalled and those that the empathizers felt from the chat. From the plots of the graphs, it can be seen that there is a highly positive correlation (the Spearman correlation coefficient is 0.806.) between the emotional valences of both the roles as the results of Section 3. On the other hand, there is low correlation (the Spearman correlation coefficient is 0.658.) between the emotional arousals of both the roles, although the correlation was slightly stronger due to the difference in instruction.



Figure 8: The relationship between the emotional valences (from low (1) to high (9)) of the emotion generators and the emotional valences (from low (1) to high (9)) felt by the empathizers from the text int the further experiment.





4.1.2 Correlation Analysis between Physiological Signals and Subjective Emotions

The power values of the three frequency bands (alpha, beta, and theta) in the EEG at three locations (Fp1, O1, and O2) and the HEG ratio at one location (Fp2) were analyzed for significant differences among the three states: resting state before the task, happy empathy, and sad empathy. As the results, there were no significant differences (p < .05) in the EEG and the HEG ratio. Although there was no significant difference, the power values of theta waves at O1 and O2 were higher than those at rest in 7 out of 8 trials as in the aforementioned experiment.

4.1.3 Integrated Analysis of Data from Two Experiments

We integrated the data from all 16 trials, including the experiment in Section 3 and this experiment, and divided them into two groups. Specifically, the seven trials in which the sum of the absolute values of the differences between the emotion generators' responses and the empathizers' responses from the text and their own emotions was less than or equal to 3 were classified as empathizable group, and the nine trials as the rest were classified as non-empathizable group, based on the results of the SAM of the participants of the two experiments.

Figure 10 and Figure 11 show the power values of theta waves at O1 and O2 for each of the two groups. The results show that the power values at O1 in the empathizable group was significantly lower than those in the non-empathizable group (p < 0.05). There was no significant difference about O2.

4.2 Discussions

From the results of responses to SAM in the two experiments, we found that emotional valence was more likely to be empathized with, even in text-based chat. On the other hand, when we instructed constraints on the degree of arousal in the further experiment, which became easier to empathize to some extent, but in general of the two experiments, arousal was not easily empathized with in text-based chat. We believe that the reason for this is that in textbased chat, there are many words to express level of arousal.

One of the reasons for the lack of significant differences in physiological signals between the resting state and the on-task state in the further experiment may be that, unlike the aforementioned experiment, the data included data from males, but since the number of data is insufficient, further additional experiments are necessary in the future.

Since the power of theta waves at O1 in the occipital region was significantly lower in the empathizers, who were similar to the emotional valence and arousal of the emotion generators, we believe that the theta waves in the occipital region can provide data for estimating that emotion generators and empathizers have similar emotions. However, since it is not a simple correlation that the power value increases when the emotions are similar, it is necessary to conduct further experiments to analyze the relationship between the value and the degree of empathy in more detail.



Figure 10: The power value of theta wave at O1 in two groups of emotion similarity difference.



Figure 11: The power value of theta wave at O2 in two groups of emotion similarity difference.

5 CONCLUSIONS

We conclude from the two experiments that the power of theta waves in the occipital region is higher during empathy for the content of a text chat than at rest, but lower when empathizing with the same emotion of an emotion generator. Moreover, we find that we need more data to analyze the differences in the measurement points of physiological signals, the relationship between EEG and HEG, and the individual differences among participants. In addition, we believe that further analysis of the content of the text chat, the degree of empathy, and the fluctuations of the physiological signals during the text chat will show possibility of using the physiological signals in more detail. CHIRA 2022 - 6th International Conference on Computer-Human Interaction Research and Applications

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