EEG-based Evaluation of Enjoyment Emotion during cognitive-motor task

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***Abstract*— Remote communication has become a widely used means of communication in modern society. However, the limited non-verbal information can make remote communication difficult, and there is a need to develop technologies that quantitatively evaluate and transfer users' emotional information for smoother communication. This study focuses on enjoyment, one of the positive emotions crucial for communication, and investigates EEG biomarkers for estimating enjoyment during cognitive-motor tasks. EEG was measured at six channels in 12 healthy young adults while they performed cognitive-motor tasks at five different difficulty levels. The task was presented as an immersive virtual reality game to simulate a virtual workspace with adjustable task difficulty. Participants answered a questionnaire to evaluate their "enjoyment" level for each gameplay. A stepwise regression analysis resulted in a linear model equation that could estimate enjoyment levels across all participants based on normalized EEG power values. This model was validated using leave-one-participant-out cross-validation, demonstrating its effectiveness in predicting enjoyment. Our findings suggest the importance of left parietal electrophysiological activity for estimating the positive emotion of enjoyment.**

I. INTRODUCTION

With the advancement of telecommunication and virtual reality (VR) technology, the opportunities for communication and collaboration in online environments have rapidly increased [1]. Compared to face-to-face communication, online meetings, remote classes, and avatar-mediated communication face challenges in efficient task assignment and smooth team communication [2] [3] due to the difficulty in obtaining non-verbal information [4]. Although research on face tracking, motion tracking, and emotion estimation from speech content has progressed [5], a method for estimating users' emotional states without relying on physical expressions or verbal information is needed to solve these problems. This is particularly relevant for online collaboration, lectures, and remote task instructions, where physical expressions or active conversations may not be present. The development of such methods could improve the ability to gauge emotional states in a wider range of contexts, potentially improving user experience and interaction in virtual and remote environments.

The effectiveness of quantitative emotion estimation using physiological information has been increasingly demonstrated in recent years. Previous studies [6] have shown that physiological information such as electroencephalography (EEG) and pulse waves can robustly estimate emotions with high accuracy, regardless of the individual, compared to facial expressions. Heart rate variability, another physiological measure of the autonomic nervous activity, is also gaining attention as an objective indicator of emotional responses and is expected to be a valuable emotional assessment metric [7]. In this study, we aimed to evaluate users' positive emotion of enjoyment during online tasks using EEG measurements, which are capable of monitoring the cognitive states of users with an excellent temporal resolution. We investigated multiple frequency components of EEG signals during the cognitive-motor task and their relationship with subjective enjoyment intensity. We also incorporated a stepwise regression analysis to determine the common biomarker signals that allow emotional evaluation of enjoyment during task engagement.

II. METHODS

Twelve healthy adults (5 males, 7 females, average age 20.8 ± 1.5 years) participated in the experiment. All experiments were approved by the institutional Ethics Committee and participants gave written informed consent before participation. Participants played five sessions of motor-cognitive tasks with different difficulty levels in a random order.

The task was an apple-catching game created by Unity engine as shown in Figure 1. An immersive VR game was selected because of its capability to adjust the task difficulty, simulate a virtual workspace, and evoke associated emotional responses. The goal of the game is to catch apples flying from the front center to either side of the player (red or blue area in Fig. 1) by moving the basket connected to the controller. The flying speed of the apple was constant throughout the game (4 m/s), and the game difficulty was adjusted by the five time intervals between the flying apples (2, 4, 6, 8, and 10 s). The shorter interval is assumed to have more enjoyment as a nature of the game. Each session lasted one minute, regardless of the difficulty levels.

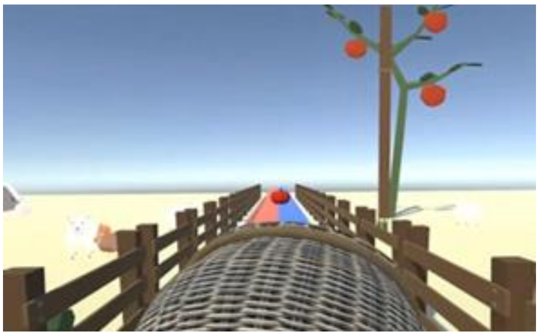

Fig.1 Motor-cognitive task: apple-catching VR game

EEG was measured during the VR games at six channels on the frontal (F3, F4), central (C3, C4), and parietal (P3, P4) regions. Participants first wore the electrode cap and a head-mounted display over the cap. After each game play session, participants completed a questionnaire to provide subjective ratings of their enjoyment. The questionnaire used a 5-point Likert scale, where '1' indicated that participants found the game the most enjoyable and would like to play it again, '5' indicated that they found the game least enjoyable, boring, or would not play it again, and '3' indicated neutrality.

We investigated the relationship between the game difficulty (time intervals between the apples) and the questionnaire scores using a Spearman's rank correlation test. The EEG data were subjected to a fast Fourier transform to calculate the power value of each channel in four frequency bands (δ, θ, α, and β bands). The channel-wise power spectrum values were further normalized to those of a session in which the participant rated their enjoyment as neutral (scale of 3) and used as indices of cortical activity. If there were two or more sessions in which they rated their enjoyment as neutral, the averaged power value was used for normalization. We used the normalized power values to examine their correlation with subjective ratings of enjoyment.

We then conducted a stepwise regression analysis to create a linear model that best approximates the score of enjoyment out of 24 different normalized power values (6 channels x 4 frequency bands) as factors of the EEG index. We compared actual questionnaire scores with predicted score values obtained by substituting EEG data into the regression equation. Furthermore, leave-one-participant-out cross-validation (LOOCV) was conducted to validate the prediction model. In the LOOCV process, data from one participant were excluded as test data. Subsequently, a linear regression model was then built using only the remaining data of other participants. Finally, the test data were substituted into the model to estimate the enjoyment scores. This process was repeated for all participants. The error between the enjoyment scores estimated from the prediction model and the actual scores was evaluated. A pipeline summarizing the experimental flow is shown in Figure 2.

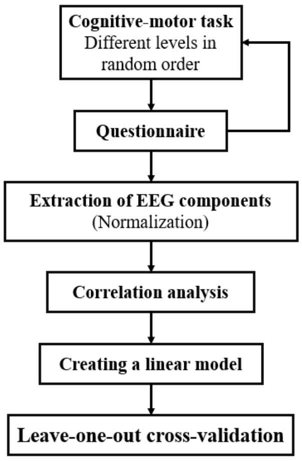

Fig.2 Experimental and analytical pipeline

III. RESULTS

Figure 3 shows the relationship between task difficulty (time intervals) and questionnaire scores (enjoyment). A significant strong positive correlation (r = 0.834, $p < 0.01$) was found between interval and enjoyment, indicating that the longer the interval, the less enjoyable and boring it is. This confirms that the enjoyment can be varied by changing the interval of the objects to interact.

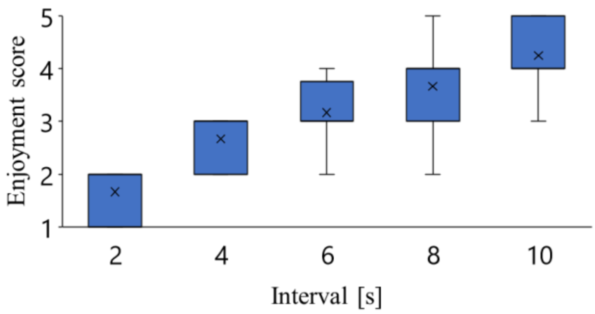

Fig.3 Relationship between task difficulty (interval) and questionnaire scores

Table 1 shows the correlation coefficients r between the subjective enjoyment obtained from the questionnaire and the normalized power values. The single asterisk indicates a statistically significant correlation at the 5% significance level, and the double asterisks denote a statistical significance at the 1% significance level. Significant positive correlations were observed in the central-parietal channels in the alpha and beta bands. Since the higher questionnaire score shows less enjoyment, these results indicate that the increased enjoyment is associated with decreased power in these channels and frequency bands. On the other hand, a broadband signal from the left frontal channel (F3), except for alpha band power, showed a significant negative correlation with the enjoyment scores. The increase in frontal spectral power may be another signature of the neurophysiological response of enjoyment.

Table 1 Correlation coefficient *r* between questionnaire scores and normalized power values

r		Channels					
		F3	F4	C3	C4	P3	P4
Frequency	Delta band	-0.25*	0.050	-0.066	-0.088	0.056	0.19
	Theta band	-0.28*	-0.12	0.027	-0.034	0.20	0.28*
	Alpha band	0.051	-0.012	0.32*	0.52**	0.58**	0.51**
	Beta band	-0.28*	-0.16	0.13	0.080	0.50**	0.39**

Table 2 shows the correlation coefficients *r* between the task difficulty (intervals) and the normalized power values. Significant and moderate correlations were also found in the central-parietal channels in the alpha and beta bands. However, there was no statistically significant correlation between task difficulty and left frontal spectral powers.

Table 2 Correlation coefficient *r* between task difficulty and normalized power values

r		Channels					
		F3	F4	C3	C4	P3	P4
Frequency	Delta band	-0.14	0.17	0.035	0.082	0.17	0.22
	Theta band	-0.17	0.013	0.11	0.13	0.24	0.31*
	Alpha band	0.13	0.038	0.38*	0.46**	0.49**	0.43**
	Beta band	-0.11	-0.10	0.23	0.21	0.48**	0.47**

A stepwise regression analysis yielded the model equation as in Equation (1). Here, x_{ij} represents the normalized power values in the frequency band i at channel j, and y represents the estimated questionnaire scores, respectively.

$$y \approx -4.7 + 0.44 x_{\delta F4} + 4.7 x_{\theta P3} + 0.97 x_{\alpha P3} + 8.1 x_{\beta P3} - 6.4\, x_{\theta P3} x_{\beta P3}. \quad (1)$$

The correlation coefficient of the model equation was 0.814 ± 0.168 (mean ± standard deviation). The result indicates that P3 is important for estimating enjoyment [8]. Figure 4 shows a comparison of the measured and predicted values for representative four participants from the LOOCV analysis. LOOCV results showed that the average error between the estimated enjoyment scores and the actual questionnaire scores was 0.37 ± 1.4. The mean and standard deviation of the participant-wise correlation coefficients between the measured and predicted scores of enjoyment were r = 0.45 ± 0.48.

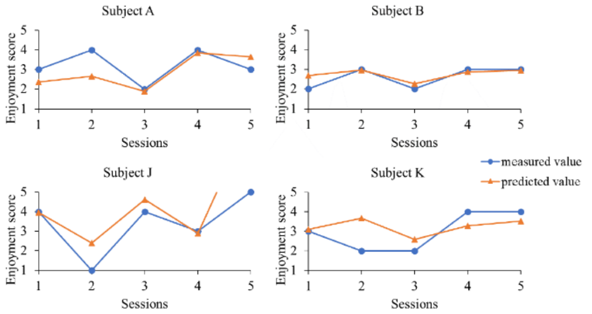

Fig.4 Comparison of measured and predicted values in representative participants.

IV. DISCUSSION

Using a VR-based cognitive-motor task of varying difficulty, the current study investigated EEG biomarker signals for the positive emotion of enjoyment. Questionnaire scores confirmed that the five pre-defined levels of task difficulty successfully elicited different intensities of enjoyment, with shorter intervals between flying objects eliciting more enjoyment. Correlation analysis and stepwise regression both indicated the importance of left parietal activity in determining the intensity of enjoyment. The deviation of the estimated enjoyment intensity from the ground truth questionnaire score was small enough to classify the predicted value into the correct level of enjoyment in most cases, suggesting the usefulness of the proposed approach.

The involvement of the left parietal lobe in positive emotional processing is consistent with the study by Dolan et al [8], who found specific activation of the left parietal lobe for happy face stimuli. Compared to the widely studied negative emotions, which are easier to discriminate into different classes, less attention has been paid to the recognition of positive emotions, which are not fully independent [9]. In recent years, studies have been conducted to classify positive emotions [10] [11], but few studies have focused on the degree of "enjoyment" within positive emotions, as in the present study.

Focusing on the large coefficients in the model equation, it is suggested that enjoyment is maximized when both the θ band and the β band are suppressed, and boredom is felt when the θ band and the β band are antagonistic. Table 1 shows that the suppression of the α band has the highest correlation with enjoyment, followed by the β band. In this model equation, the β band becomes a stronger feature by taking the product with θ band.

However, from Tables 1 and 2, significant correlations with normalized power values were found not only with the enjoyment scores from the questionnaire but also with the speed of the game, suggesting that the brain activity related to game speed may have confounded the results, rather than brain activity related to enjoyment alone. Because the parietal area is part of an association area that combines and processes multimodal sensory and motor information, it may have been activated by engagement with the task [12]. The task design needs to be improved in future studies to simulate conditions with different levels of enjoyment while ensuring that the required motor responses remain comparable. Another area for improvement is the use of the good temporal resolution of the EEG. While we derived the feature EEG values as average power over the whole minute of gameplay, there may have been changes in emotional states during a session. The time-frequency analysis of the EEG data can be combined with a more fine-grained online or post-hoc subjective rating [13] to further improve the quality of the annotation and the accuracy of the model.

V. Conclusions

The current study used a VR-based cognitive-motor task of varying difficulty to investigate EEG biomarker signals associated with the positive emotion of enjoyment. The results indicated that left parietal activity plays a significant role in determining the intensity of enjoyment. The emotion of enjoyment may be represented by complex combination of electrophysiological responses. Suppression of the α band showed the highest correlation with enjoyment, followed by the β band, with the combination of θ and β bands. While caution should be taken regarding differences in game speed that may affect the results, the LOOCV results demonstrate the potential of using EEG to estimate the positive emotion of enjoyment. Future research should focus on refining task design to better isolate emotional responses and taking advantage of the high temporal resolution of EEG for more detailed analysis of emotional dynamics.

VI. Acknowledgment

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