A QoE Physiological Measure of VR with Vibrotactile Feedback based on Frontal Lobe Power Asymmetry

Yan Zhang, Yuning Su, and Xiaoying Sun, *Member, IEEE*

***Abstract*—Quality of experience (QoE) has been widely recognized as the primary metric to evaluate user experience in multimedia applications. However, the QoE assessment of tactile virtual environments is still highly dependent on subjective measures. Inspired by the fact that physiological signals can characterize the user's emotional state, we propose a QoE measurement method for virtual reality (VR) with vibrotactile feedback based on frontal lobe power asymmetry (FLPA). The subjective score of vibrotactile experience in VR is used as the ground truth of QoE. The selection of QoE measurement indicators consists of two steps. First, the relationship between FLPA phenomenon and scores of QoE is preliminarily established by statistical methods and Spearman Correlation Coefficient. Then, the most important FLPA feature is selected by random forest, which is the best indicator for QoE measurement. The brain neural images show that vibrotactile feedback in VR can evoke FLPA phenomenon. Correlation analysis shows that there is a significant correlation between subjective scores of QoE and FLPA features. The classification results show that the selected best FLPA feature can be used as a physiological indicator to measure and predict QoE. We achieve mutual interpretation of EEG-based physiological measurements and subjective cognitive outcomes of QoE.**

***Index Terms*—Quality of experience, virtual reality, vibrotactile feedback, physiological measurement, frontal lobe power asymmetry.**

I. INTRODUCTION

Virtual haptic feedback has great potential in improving the realism and richness of the user interaction experience in virtual reality (VR) [1]-[3]. Quality of experience (QoE) of haptic virtual environments is an evolving research topic and taking QoE as the primary metric to evaluate VR experience has been generally accepted by researchers [4], [5]. Compared to vision and hearing, the technology to measure the impact of vibrotactile feedback on VR experience is still immature [6], especially the objective QoE measurement method.

In the process of interaction with multimedia applications, users focus on the overall feeling of multi-dimensional sensory information integration. QoE is an overall metric of the quality of interaction between users and multimedia applications, which can be measured in many ways [2]. The International Telecommunication Union (ITU) defines QoE as the end-user overall subjective acceptability of applications or services [7]. According to the definition of QoE, scholars have classified different measurement parameters to meet the actual assessment needs. Without considering the impact of quality of service on user experience, we summarize the QoE evaluation methods as psychometric and physiological measures.

Psychological measurement is a user-centered means to reflect the user's psychological state through user feedback. The parameters of psychological measurement in VR applications include cybersickness [8], immersion [1], [9], emotion [10], etc. Psychometry is a subjective assessment method, which reflects the unique perception state of each user through questionnaires. ITU recommends using mean opinion score to measure QoE [11], [12]. A specific group of subjects used a scale to subjectively score the videos watched in a specific environment, and the mean score of all subjects was used to represent the QoE [11]. Subjective evaluation is currently the mainstream method of QoE measurement [13]-[15], which reflects users' subjective feelings to a certain extent. But these methods rely on prior knowledge and conscious responses and often fail to provide insight into the underlying perceptual and cognitive processes. When questionnaires or scales do not reflect their inner feelings well, subjects may not be able to accurately express their assessments.

Unlike questionnaires, physiological measurements reflect the state of users by directly measuring their implicit biological parameters. The effectiveness of some biological means has been verified in the QoE evaluation of multimedia applications, such as electroencephalography (EEG) [5], [10], [16], heart rate [4], [10], electrocardiography [9], etc. EEG is a minimally invasive electrophysiological measurement of scalp voltage changes. As a physiological measure of QoE [16], EEG has been widely used in visual and auditory research. Tao et al. [17] used the brain wave oscillations induced by negative emotions to calculate the user tolerance time for video rebuffering and then optimized the video rebuffering parameters to maximize QoE. Lin et al. [18] used ERP features evoked by traffic lights in the virtual dynamic driving environment to quantitatively evaluate the cognitive response of drivers and concluded that ERP can reflect the cognitive state. These studies using EEG to characterize the emotional state of users have provided a reference for our interest. However, their methods exploit the transient responses of brain potential [19], which may be limited in complex VR applications.

- This work was supported by the National Natural Science Foundation of China under Grant 61631010. The corresponding author is Xiaoying Sun.
- Yan Zhang and Xiaoying Sun are with the College of Communication Engineering, Jilin University, Changchun, China, 130012, E-mail: yanz19@ mails.jlu.edu.cn; sunxy@jlu.edu.cn.
- Yuning Su is with the School of Artificial Intelligence, Jilin University, Changchun, China, 130012, E-mail: suyn19@mails.jlu.edu.cn;

At present, researchers have begun to pay attention to the application of tactile feedback in VR [5], [8], [10]. To the best of our knowledge, studies assessing how vibrotactile feedback affects the VR experience still rely on subjective measures [8], [20]. There have been several studies exploring the use of EEG to identify haptic information. Golnaz et al. [21] used nonlinear features of EEG signals to successfully recognize three friction states during haptic interaction: dynamic, static, and no-friction. The maximum classification accuracy achieved was 78%. Özdenizci et al. [22] introduced an invariant representation learning network to identify three different types of textured surfaces with varying roughness levels in the process of active tactile detection. They achieved a classification accuracy of 70%. These studies collectively demonstrate the potential of EEG in analyzing tactile objects. However, whether these theories can be applied to evaluate the haptic experience in VR scenes remains to be further analyzed.

Emotion is a psychometric parameter of QoE, which can be reflected by physiological means of EEG [5]. Emotional terms are relative to the users, not the experience, which is the comprehensive expression of multiple sensory information [23]. The subjective feeling caused by external stimuli will be reflected in the EEG signal synchronously according to the physiological mechanism of brain convergence [24]. The feeling is the internal component of emotions and can be evoked by tactile stimuli [19]. It may be feasible to measure emotion by EEG to reflect the QoE of VR with vibrotactile feedback. Brain frontal lobe power asymmetry (FLPA) is the most studied and has a relatively mature theory among the many EEG-based measures of emotion. In the early stages of research on physiological measures of QoE in VR with vibrotactile feedback, choosing FLPA to measure emotion and reflect QoE is helpful for the development of research issues.

The idea that FLPA can reflect emotional states [25] has been applied in many aspects. From the perspective of cognitive nerve, Reznik et al. [26] discussed the feasibility of FLPA to reflect the brain nerve correlation and psychological structure of users in the form of a review. Wacker et al. [27] used FLPA to measure emotional states and found that FLPA evoked by positive emotions had a strong correlation with state stability and flexibility of desire motivation. Thus, FLPA may have the potential to achieve mutual interpretation between physiological responses and psychological perception. In the application of emotion recognition, Moghimi et al. [28] used FLPA to classify user emotions in an audio-visual VR environment and obtained a satisfactory accuracy of emotion recognition. This may indicate that FLPA has strong environmental applicability. However, FLPA still has a lot of room for improvement. Petrantonakis et al. [29] introduced multi-dimensional directional information into the FLPA calculation method to improve the accuracy of emotion recognition. These studies provide theoretical support for using FLPA to evaluate the QoE of VR with vibrotactile feedback.

In this paper, we use subjective measurement as the ground truth of QoE to verify the feasibility of the existing biological means to measure the QoE of VR with vibrotactile feedback. We focus on the EEG-based physiological measurement of QoE and apply it to the QoE evaluation of VR vibrotactile feedback. The scale score and FLPA are used to measure the emotional psychological and physiological characteristics of the users, and the correlation between them is tested. A classification experiment is designed to verify the feasibility of FLPA as a QoE evaluation indicator. Our work fills a gap in the physiological measurement method of QoE for vibrotactile feedback in VR. User perception in the process of interaction with VR is multi-factor, and subjective scoring alone may not fully reflect the real measurement of user experience. Our study aims to complement rather than replace existing psychometric measures. We expect to contribute to the improvement of the subjective and objective evaluation system of QoE. The main contributions are summarized as follows:

- We propose a new physiological measure of QoE for multimedia applications. To our knowledge, this should be an early study of objective evaluation methods for QoE in virtual scenes with audio-visual touch 3-dimensional information input.
- We find that using vibrotactile feedback of different qualities in VR can evoke different FLPA phenomena in the brain. Correlation analysis shows that FLPA features are significantly correlated with the subjective scores of QoE.
- We introduce random forest to rank the FLPA features of different rhythms and positions according to their contribution to QoE evaluation of VR with vibrotactile feedback. The dichotomous results of positive and negative emotions indicate that FLPA can be used to measure and predict QoE in multimedia applications.

The remainder of this paper is organized as follows. Section II introduces FLPA and the corresponding feature selection method. The detailed design of the user study is described in Section III. Section IV shows the experimental results and analysis. Some discussions are presented in Section V. Section VI gives the conclusion of this paper.

II. Method

We inherit the view from [5] that emotion is a psychometric parameter of QoE and we expect to find an EEG-based emotion measure to evaluate the QoE of VR with vibrotactile feedback. To determine the specific indicators used to measure QoE, we carry out our work from three aspects. The significance of correlation preliminarily confirms the intrinsic relationship between FLPA features and subjective scores of QoE. The FLPA features are ranked according to their importance to QoE prediction, and the most important feature is used as the best indicator to measure QoE. Classification error is used to test the performance of the selected indicators in evaluating QoE. The whole process of selecting QoE physiological measurement indicators is shown in Fig. 1. In this section, the FLPA is first introduced, and then the three aspects mentioned above are described in detail.

A. Frontal Lobe Power Asymmetry

The right prefrontal lobe of the brain is thought to be involved in emotional functioning. Positive emotions have an inhibitory effect on the right cortical network, and there will be an asymmetry phenomenon of the left-side power higher than the right-side power in the prefrontal lobe [30, 35]. When the

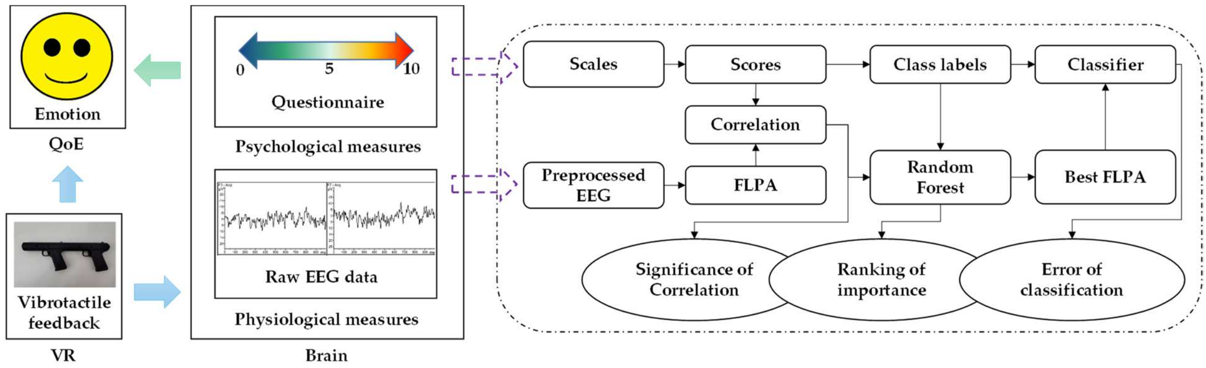

Fig. 1. The whole process of selecting the physiological measurement indicators of QoE.

users have positive emotions about a VR application, they generally give higher than the average subjective evaluation. In this case, the two measures may be related in some way. In psychology, emotions are usually analyzed in a two-dimensional valence/arousal space [31]. According to the valence dimension of the valence/arousal space, the left lateralization of frontal lobe power represents positive emotion, while the right lateralization of frontal lobe power represents negative emotion [29]. The value of FLPA represents the degree of lateralization. These representations correspond to the subjective evaluation of QoE in the form of a scale, and the specific relationship between them is the focus of this paper.

In the numerous theoretical studies of FLPA, there is no unified conclusion about which rhythm of EEG and which spatial location in the brain are related to emotion. According to the review literature [26], different from the frequency band of 8-12Hz used by Davidson [25], most of the later studies [32], [33] chose 8-13Hz as Alpha rhythm. Other studies have demonstrated the feasibility of rhythms other than Alpha to reflect emotions, including Theta (4-7Hz) [30], Beta (14-30Hz) [34], and Gamma (31-100Hz) [35]. Many studies have shown that brain regions associated with emotion include F3-F4 [33], F5-F6 [36], and F7-F8 [32]. Since the specific rhythm and spatial position of the brain that can reflect emotions could not be determined, all the common rhythms and electrodes are used. The rhythms include Theta (4-7Hz), Alpha (8-13Hz), Beta (14-30Hz), and Gamma (31-100Hz). Electrodes include F3-F4, F5-F6, F7-F8. In addition, we also studied the continuous frequency bands of these four rhythm combinations, including 4-13Hz, 4-30Hz, 4-100Hz, 8-30Hz, 8-100Hz, and 13-100Hz. The new rhythms are named TA, TAB, TABG, AB, ABG, and BG by combining the initials of all the bands it contains. The combination of two electrode pairs and the combination of three electrode pairs are added in the spatial position. Therefore, we use 10 rhythms and 7 spatial locations to get a total of 70 FLPA features.

Davidson mentioned in [25, 30] that the calculation method of FLPA is

$$A^{Da.} = \frac{P_L - P_R}{P_L + P_R}, \tag{1}$$

where P_L is left frontal lobe power and its corresponding electrodes are F3, F5, and F7; P_R is right frontal lobe power and its corresponding electrodes are F4, F6, and F8. Reznik summarized in [26] that most of the subsequent researchers adopted the logarithmic method, and the formula is

$$A^{Re.} = \ln\left(\frac{P_L}{P_R}\right). \tag{2}$$

We test both computations in Section IV to determine which one better suited our needs.

EEG data is first bandpass filtered (FIR) at 4-100Hz, after which the average of left and right earlobes is applied as a re-reference. Then we manually remove the blinking instances according to the independent component analysis.

B. Correlation

The subjectively measured data do not conform to a normal distribution according to the analysis in Section IV. Therefore, the Spearman Correlation Coefficient (SCC) is calculated to represent the correlation.

Let $\mathbf{X} = \{x_n\}$ and $\mathbf{Y} = \{y_n\}$, $n = 1, 2\cdots, N$ denote two sets of data in the form of column vectors of length N. SCC is equivalent to Pearson's Linear Correlation Coefficient (PLCC) applied to the rankings of $\mathbf{X}$ and $\mathbf{Y}$. SCC can be calculated as

$$r = \frac{\sum_{n=1}^{N}\left(R_{x_n} - \frac{N+1}{2}\right)\left(R_{y_n} - \frac{N+1}{2}\right)}{\sqrt{\sum_{n=1}^{N}\left(R_{x_n} - \frac{N+1}{2}\right)^2}\sqrt{\sum_{n=1}^{N}\left(R_{y_n} - \frac{N+1}{2}\right)^2}}, \tag{3}$$

where R_{x_n} is the rank value of x_n. Since the rank values are sequential from 1 to N, the mean of all the rank values is $(N+1)/2$.

C. Random Forest

Random forest (RF) is an ensemble learning algorithm based on a decision tree. The details of RF ideas and construction methods can be found in many studies [9]. We only introduce how to rank FLPA features according to their importance to QoE evaluation.

Each sampling generates a sample set, and the remaining samples in the total sample that have not been sampled are called out-of-bag (OoB) data. OoB data error can be used to measure the importance of features. The calculation of feature importance consists of two steps:

Step 1: After learning M trees of RF, use each tree to calculate the classification error of corresponding OoB data, which is denoted as $\{Err_m\}$, $m=1,2,\cdots,M$.

Step 2: Randomly add some noise to the i th feature (or randomly sort the value of the current feature), and calculate the classification error again for the OoB data with noise to get $\{Err_m^i\}$. Then the calculation formula of feature importance is

$$import_i = \frac{1}{M}\sum_{m=1}^{M}\left(Err_m^i - Err_m\right). \tag{4}$$

The larger $import_i$, the more important the i th feature is. Through the above two steps, each feature is given a value that represents its influence on the classification result. Features with low importance have little influence on the classification results of OoB data, and adding noise will not change the classification error much theoretically. However, adding noise to important features will lead to significantly higher classification errors. This explains the rationality of OoB data error to measure the importance of features.

D. Classifier

Classification is a way to verify the validity of features. The classifier trained with the selected optimal FLPA can be used to predict the subjective score representing emotions. The feasibility of EEG-based physiological measurements for evaluating QoE is verified when the prediction accuracy reaches an accepted range. Classifiers including linear discriminant analysis (LDA), K-nearest neighbor (KNN) (K =7), naive Bayes (NB), and support vector machine (SVM) are used for the classification tasks.

The performance of all classifiers is assessed using the Leave-One-Out (LOO) cross-validation method [21]. LOO is a method of training and testing a classifier using all the data in a dataset. All L samples in the dataset are divided into two parts, the first with $L-1$ samples is the training set, and the remaining part with one sample is the test set. Each sample will be used as the test set once, and there will be L iterations.

All FLPA features are employed as inputs for the classifier, while emotion labels serve as outputs of the classifier. For a single sample, the prediction is either true or false. The classification accuracy is calculated by

$$acc = \frac{L_{Cor}}{L}, \tag{5}$$

where L_{Cor} is the number of correct predictions.

III. User Study

Emotion is a parameter of QoE, which can be measured by subjective scores or reflected in EEG. We conducted a user study using vibration stimuli of different frequencies to explore the characteristics of users' neural responses under different qualities of tactile feedback in VR and to analyze the correlation between physiological and psychological measures of VR experience.

A. Apparatus

Shooting games, as a common application in VR, are chosen to test our idea. The controller that can provide vibration stimulation is independently designed by the research group, and its details are described in [37]. The controller can provide continuous vibrotactile feedback when the finger pulls the trigger without release. The vibration frequency of the controller is adjustable between 0 to 60Hz. Vibration frequency is the only variable in the user study, and the frequencies used in this paper include 0Hz, 1Hz, 15Hz, and 60Hz. 0Hz indicates no vibration stimulus. We fix two identical controllers together to simulate the appearance of an automatic rifle. The vibration feedback provided by the controllers is a rendering of the directional force perception, simulating the recoil during shooting. The parameters of the rifle simulated by the controllers are shown in TABLE I.

TABLE I
THE PARAMETERS OF THE RIFLE SIMULATED BY THE CONTROLLERS

Force feedback			Weight (g)	Size (cm)
Form	Magnitude (N)	Rate (Hz)		
Recoil	23	0, 1, 15, 60	501.8	$33\times 13.5\times 4$

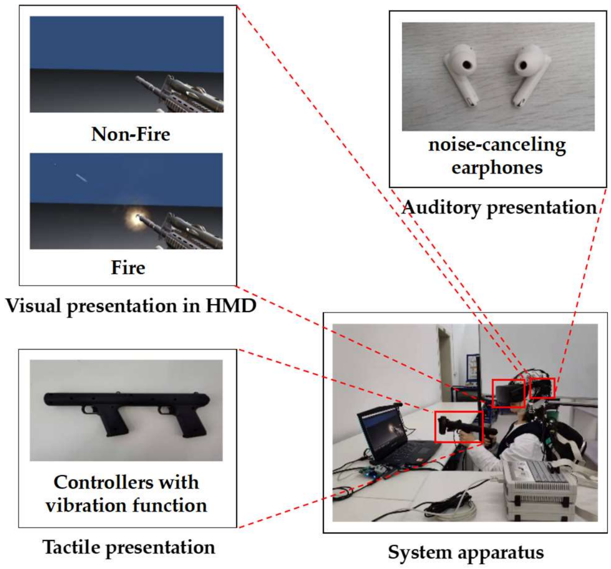

Fig. 2. The experimental environment. The subject wearing an Oculus Rift and EEG cap seats comfortably in front of the table and interacts with the rifle simulated by the controllers.

To keep the original environment of VR while reducing the visual effects on the EEG, we choose a relatively simple visual interaction interface. The visual interface is presented through a head-mounted display (HMD). When the user pulls the trigger to the sky or ground, there is a visual effect of bullet flight in HMD. The gun displayed in HMD looks like M4A1. The theoretical rate of fire of real M4A1 is 600-900rpm, corresponding to visual shooting frequencies of 10-15Hz. Compared with the extreme frequencies of 1Hz and 60Hz, the 15Hz vibration stimulus could theoretically provide the highest realism in the selected VR presentation scene. Instead of using the HMD's headset, we use noise-canceling earphones to ensure that the subjects are not affected by the vibrational sound of the controller. We used the whole set of Oculus devices, which have a published latency of less than 20ms. To minimize the increase of VR interaction delay, Oculus Touch is fixed to the front end of the controller as a locator. Fig. 2 shows an overview of the experimental environment.

Brain activity is acquired using a 64-channel EEG amplifier (Brain Amps, Brain Products, Germany) and is recorded using a Brain Vision Recorder (Brain Products, Germany) with a 1000Hz sampling rate. The EEG cap consists of 64 actiCAP active electrodes (Brain Products, Germany) positioned in line with the 10-20 system. Electrode FCz is used as the reference. Signal denoising and other preprocessing processes are completed by Brain Vision Analyzer 2.2 (Brain Products, Germany). The rest of the analysis is done by MATLAB2018b.

B. Subjects

Thirty-two right-handed subjects (18 male) from Jilin University, aged 20 to 27 (Mean=23.84, Standard Deviation=1.78), with a bachelor's degree or above, are recruited. Of the selected 32 subjects, 22 had fired live ammunition at least five times (18 with rifles and 12 with handguns). The remaining 10 had at least five years of experience playing virtual shooters on the terminal. They were all interested in shooter games on virtual terminals and had a general understanding of the differences between real shooting sports and virtual shooting games. All participants had experienced shooting games in a VR environment before and had no dizziness reaction to VR. Before the experiment, the subjects had a certain understanding of the experiment content and signed an informed consent. The experimental procedure is approved by the ethical committee of Jilin University.

C. Questionnaire

Most parameters of QoE can be measured by questionnaires. In this paper, a questionnaire is designed to evaluate the emotional parameter of QoE. The questionnaire contained six question items. The words used to describe emotional states in the first five question items are shown in TABLE II. In each question item, subjects are required to determine a score from an 11-point scale that corresponded to their emotional state during the VR experience. Scores range from 0 to 10, with 0 representing the most negative and 10 indicating the most positive. A score of 5 indicates a neutral emotion. In the sixth question item, participants are asked to judge "Do the emotional descriptors used in the first five question items accurately reflect your emotional state?". If the answer is "no", the subject is asked to provide more reasonable words to describe the emotion.

The subjects can make voluntary statements after filling out the questionnaire. The content of the statement could be a question about the task, a description of feelings, a suggestion for the experiment, anything of interest, etc. The assistant records the content of the voluntary statements of the subjects and confirms the questionnaire results with the subjects again.

D. Protocol

In this paper, we use a common protocol to evoke EEG steady-state response, i.e., continuous periodic stimulus protocol at a certain rate [19].

TABLE II
WORDS DESCRIBING EMOTIONAL STATES IN THE QUESTIONNAIRE

Item No.	Negative (0 - 4 points)	Positive (6 - 10 points)
1	Dissatisfied	Pleased
2	Upset	Happy
3	Bored	Interested
4	Withdrawal	Approachable
5	Disgusted	Liked

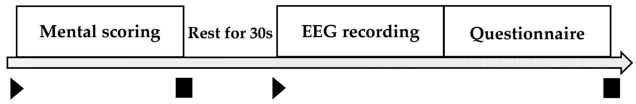

Fig. 3. The entire experimental process of a single subject. Black triangles and rectangles represent the start and end of a single experiment session, respectively.

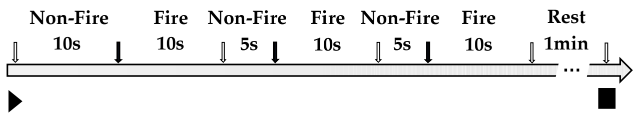

Fig. 4. The experimental protocol for mental scoring and EEG recording. The downward arrow represents EEG markers in the process of EEG recording, where black and white represent the start and end of pulling the trigger, respectively.

In preparation, the subjects do familiarity training in the VR environment with only audio-visual feedback, including game operation, firing mode, user experience, etc. Through mental count training, subjects try their best to ensure that the mental count corresponds to the time. The subjects are told other precautions, including keeping their wrists still as much as possible and not blinking when pulling the trigger, and only asking questions when not pulling the trigger. In addition, the subjects adjust the seats independently to ensure a comfortable experience environment.

The formal experiment is divided into mental scoring and EEG recording, as shown in Fig. 3. Each trial follows the same protocol, as shown in Fig. 4. Before each trial, the subjects are told the frequency of the vibration stimulus. After receiving the prompt to start the experiment, the subjects begin to mentally count and fire or not fire according to the set time rules. The finger should keep pulling the trigger while firing. After the third firing, one trial is over. We limit the single trial to 50 seconds. No vibration is applied for the first 10 seconds of firing, and its experience serves as a reference for subsequent QoE assessments of vibration stimuli. The same vibration stimulus is applied for the next two 10 seconds of firing, which are the object to be evaluated. The time is controlled by mental counting. There should be at least 1 minute between the two trials to eliminate the effects of the previous trial.

In the mental scoring process, the subjects are asked to quantitatively evaluate the emotional states of the VR experience under different vibration stimuli. The subjects could independently choose any optional vibration frequency to re-run the trial until all the vibration stimuli are scored in the mind. After 30 seconds of rest, the EEG recording is performed, and each vibration stimulus is applied once at the controllers in random order. When the subject begins to pull the trigger, the EEG data is synchronously marked once. The data for subsequent analyses are EEG from the third firing of each trial. The score is a reference-based relative result, so we correct the data by subtracting the brain power of the first firing from that of the third firing for each trial. The subjects begin filling out questionnaires immediately after EEG recording.

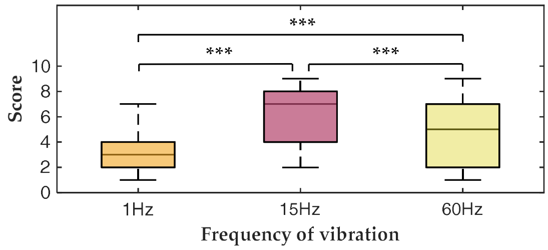

Fig. 5. Statistical results of the scores used to evaluate emotional states. Repeated Measures ANOVA is used to analyze the rating difference between vibration stimuli at different frequencies, and Bonferroni-Holm analysis is used for pair-wise post-hoc tests. "***" represents $p < 0.001$.

IV. Results and Analysis

The subjective measurements and FLPA phenomena under different vibration stimuli are first analyzed statistically in this section. SCC and RF are used to analyze the relationship between FLPA features and subjective ratings. The FLPA features that can be used as QoE evaluation metrics are identified. Finally, the effectiveness of the selected evaluation indicators is verified by the classification task.

A. Subjective Measure

Subjects use a scale to measure the emotional state of their VR experience. The evaluation results of the rationality of the questionnaire are shown in TABLE III. According to TABLE III, the questionnaire we used in the user study is reliable and valid. In response to the sixth question item of the questionnaire, 29 subjects believed that the first five question items in the questionnaire could well describe their emotional state. Only 3 people indicate that adding more question items might better reflect their feelings. Two of them mention the words: "excited", "intense" and "focused". These three words describe the arousal dimension of emotional states [31], which is rarely mentioned in FLPA research. The remaining one cannot provide a more appropriate word. Therefore, it is reasonable to use the subjective score as the ground truth to reflect the quality of tactile feedback.

TABLE III
Assessment of the Rationality of the Questionnaire

Reliability	Validity	
Cronbach	Kaiser-Meyer-Olkin	Bartlett's test of sphericity
$\alpha = 0.9170$	KMO=0.9080	$p = 0.0000$

The overall statistical results of the ratings of 5 question items in the questionnaire concerning emotional evaluation are shown in Fig. 5. There is a significant difference between the ratings of vibration stimulation at different frequencies. The rating of the 15Hz vibration stimulation is significantly higher than that of the other two frequencies, which is consistent with our hypothesis that the 15Hz vibrotactile feedback can render the best realism. The emotional state of the subjects under 1Hz vibration stimulation is basically negative, indicating that inappropriate vibrotactile feedback in VR would lead to poor user experience. The evaluation results of the 60Hz vibration stimulus are quite different. The poor concentration of scores for the 60Hz vibration stimulation may indicate that subjects could not agree on the experience of applying high-frequency vibrotactile feedback on the simulated gun.

According to the voluntary statements of the subjects, some subjects with multiple live firing experiences perceive a large gap between the rifle simulated by controllers and the real gun. But they also think the controllers are good for gaming applications. Most of the subjects are exposed to VR with haptic feedback for the first time, and they believe that controllers with reasonable parameter settings would improve the QoE of VR. In general, the three vibration stimuli correspond to the "good", "general" and "bad" three results of the rendering, and also correspond to the "positive", "neutral" and "negative" three emotional states of the VR experience. Therefore, we conclude that it is reasonable to use the selected vibration stimuli to analyze the relationship between physiological and psychological measures of QoE.

B. FLPA Phenomenon

FLPA phenomenon appears in the brain neural images of the subjects under different vibration stimuli in VR scenes. Considering that different subjects have different FLPA phenomena in response to vibrotactile feedback, we take a random subject's brain neural image as an example, as shown in Fig. 6, to analyze the relationship between the scores and FLPA phenomena.

Neural images of different rhythms show different asymmetries in response to different vibration stimuli. Theoretically, higher power in the left frontal lobe means the subject has positive emotions [29], corresponding to an evaluation score higher than 5. Some of the phenomena are roughly consistent with the scores. In the example, left frontal lobe power is higher for all rhythms under 15Hz vibration stimulation, while the subject gave a rating greater than 5. However, some FLPA phenomena do not correspond to the score completely. For example, the right frontal power of the Gamma rhythm is obviously higher in response to 60Hz vibration stimulation, but the subject gave a rating higher than 5. In addition, the FLPA phenomena of all brain rhythms are

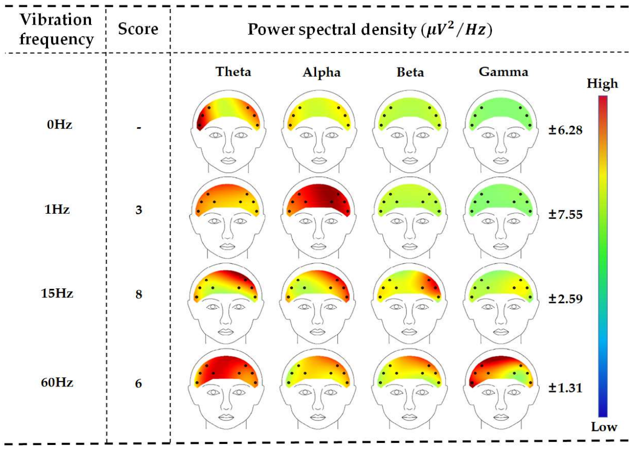

Fig. 6. An example of FLPA phenomenon under different vibration stimuli in VR.

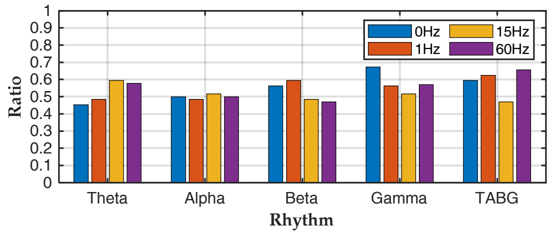

Fig. 7. The proportion of samples with higher left frontal lobe power in all samples under different vibration stimuli.

not obvious without vibration stimulation. It may be that a large amount of training makes the subjects have no emotional changes for VR without vibrotactile feedback.

In the experience of VR with vibrotactile feedback, the brain FLPA of subjects may contain information about feelings. The FLPA phenomenon of the subjects used as an example is not unique. However, the electrode location and brain rhythm of the emotion-reflecting FLPA are not always the same for each subject. The proportion of people with relatively higher left frontal lobe power in all samples under different vibration stimuli is counted, and the statistical results of partial rhythms are shown in Fig. 7. If the subjective score shown in Fig. 5 is taken as the basis, the ratio corresponding to the 15Hz vibration stimulus should be greater than 0.5, while the ratio corresponding to the 1Hz vibration stimulus should be less than 0.5. The subjective score of the 60Hz vibration stimulus fluctuated greatly, and the corresponding ratio could not be determined temporarily. Only Theta and Alpha rhythms in Fig. 7 can meet the above conditions. Therefore, the optimal FLPA for QoE evaluation should be located in these two rhythms. It is worth noting that the ideal 0Hz vibration stimulation cannot induce FLPA, which is not consistent with the results in Fig. 7. It is necessary to use the neural images of 0Hz vibration stimulation to correct the brain maps of other frequency vibration stimuli in our study.

Based on the above analysis and the fact that only vibrotactile feedback is set as the stimulus variable in the user study, we conservatively believe that different vibration stimuli are the main factors leading to different FLPA. It also can be concluded that there is a certain internal relationship between some FLPA features of measuring emotion and subjective scores of measuring QoE in VR experience with vibrotactile feedback. Our purpose is to establish the relationship between the above two and determine the specific FLPA features to measure emotion to reflect QoE.

TABLE IV
THE RESULTS OF SCC BETWEEN FLPA AND SUBJECTIVE SCORES (11-POINT SCALE)

		Theta	Alpha	Beta	Gamma	TA	TAB	TABG	AB	ABG	BG
F3-F4	Sig. (2-tailed)	**1.128E-5**	**1.009E-9**	**0.0078**	0.0619	**4.027E-8**	**7.466E-5**	**0.0133**	**2.482E-4**	**0.0144**	**0.0215**
	Correlation	0.3110	0.4227	0.1916	0.1350	0.3834	0.2819	0.1783	0.2615	0.1764	0.1658
F5-F6	Sig. (2-tailed)	**3.048E-6**	**2.08E-10**	0.0850	0.5749	**3.38E-10**	**1.109E-4**	0.3848	**3.765E-4**	0.5602	0.2872
	Correlation	0.3295	0.4381	0.1246	0.0407	0.4335	0.2753	0.0631	0.2541	0.0423	0.0772
F7-F8	Sig. (2-tailed)	**2.418E-7**	**6.65E-15**	**1.267E-5**	**0.0074**	**3.08E-13**	**8.07E-10**	**7.747E-4**	**1.875E-9**	**6.166E-4**	**0.0010**
	Correlation	0.3623	0.5235	0.3093	0.1926	0.4946	0.4249	0.2406	0.4165	0.2449	0.2356
F3-F4 F5-F6	Sig. (2-tailed)	**4.071E-8**	**1.63E-14**	**0.0195**	0.4553	**4.40E-13**	**1.429E-6**	0.3975	**9.750E-6**	0.3176	0.2769
	Correlation	0.3833	0.5170	0.1685	0.0542	0.4917	0.3397	0.0614	0.3132	0.0725	0.0789
F3-F4 F7-F8	Sig. (2-tailed)	**2.45E-10**	**2.60E-18**	**3.002E-5**	**0.0020**	**9.40E-17**	**1.61E-10**	**2.465E-4**	**6.01E-10**	**2.261E-4**	**3.724E-4**
	Correlation	0.4366	0.5753	0.2963	0.2214	0.5527	0.4406	0.2616	0.4279	0.2632	0.2543
F5-F6 F7-F8	Sig. (2-tailed)	**3.390E-9**	**2.55E-19**	**1.783E-4**	**0.0303**	**2.91E-17**	**1.11E-11**	0.1218	**3.19E-10**	0.0662	**0.0060**
	Correlation	0.4104	0.5890	0.2673	0.1564	0.5603	0.4648	0.1121	0.4340	0.1329	0.1975
F3-F4 F5-F6 F7-F8	Sig. (2-tailed)	**8.87E-11**	**8.40E-22**	**2.303E-4**	**0.0295**	**6.02E-19**	**1.36E-11**	**0.0240**	**2.75E-10**	**0.0152**	**0.0059**
	Correlation	0.4461	0.6203	0.2628	0.1572	0.5840	0.4630	0.1629	0.4355	0.1749	0.1981

The bold number indicates $p<0.05$.

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C. Feature Selection

There is a strong correlation between the EEGs of different rhythms and different positions. However, not all FLPA features are effective in measuring QoE. Among the FLPA features that can reflect emotion, one or a set of features may be the best choice to evaluate QoE. Therefore, it is necessary to select features of FLPA.

To preliminarily screen the features of FLPA that can measure QoE, correlation analysis is conducted between FLPA features and subjective scores. The result of the One-sample Kolmogorov-Smirnov test (H = 1, p = 8.5461E-06) shows that the score data did not conform to a normal distribution, so SCC is used for subsequent correlation analysis. Corresponding to Eq. (1) and Eq. (2), we name the FLPA calculation method as Subtract and Logarithm, respectively. Since SCC is a rank correlation coefficient, the correlation results between the subjective score and FLAP obtained by these two methods are the same, as shown in TABLE IV. To facilitate the description of specific FLPA feature, we name each FLPA feature according to its row and column in TABLE IV. In addition, column 10 is denoted by 0. For example, the FLPA feature in row 6, column 10 of TABLE IV is named F_{60}.

It can be seen that most FLPA features are significantly correlated with subjective scores. From a rhythmic perspective (columns), some FLPA features containing Beta or Gamma bands are not significantly correlated with subjective scores. It may be that the FLPA of Theta and Alpha or a combination of both can more accurately reflect the user's QoE. The Alpha rhythm (column 2) has the highest correlation coefficient at all locations, but the correlation decreases when combined with other bands. It can be explained that FLPA features in other frequency bands are equivalent to signals with low signal-noise-ratios, and the addition of noise interference makes the correlation of Alpha rhythm smaller. From a positional perspective (rows), there is a significant correlation between subjective scores and FLPA features including electrode pairs F7-F8. The FLPA at the electrode pairs F7-F8 may contain more user experience information. Most combinations of electrode pairs have higher correlation coefficients than single electrode pairs. It can be interpreted that there is no inclusion relationship between the user experience information reflected by FLPA at different locations, and the combination of electrode pairs achieves the mutual complement of user experience information. We can conclude that Alpha is the best frequency band to reflect user experience, and each electrode pairs contains unique sensory information. The FLPA feature F_{72} with the largest correlation coefficient in TABLE IV is probably the most important feature that can be used to measure QoE.

RF is further used to analyze the importance of each FLPA feature. Due to the randomness in each process of RF, we use the average value of feature importance calculated ten times as a reference to rank the contribution of different FLPA features to QoE evaluation. Considering the page size limitation, we visually rank the top 20% of important FLPA features, as shown in Fig. 8. Under the two calculation methods of FLPA, F_{72} makes the largest contribution to the classification, followed by F_{75} and F_{62}. These conclusions are consistent with those in

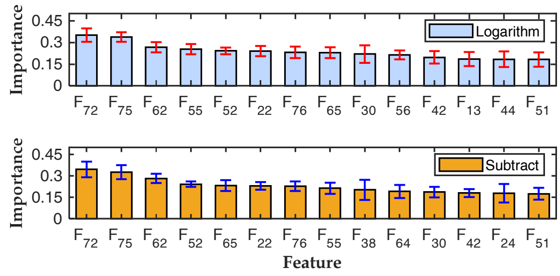

Fig. 8. The top 20% of FLPA feature importance ranking results (11-point scale).

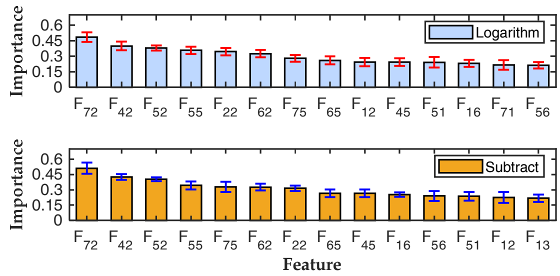

Fig. 9. The top 20% of FLPA feature importance ranking results (2-point scale).

TABLE IV.

However, taking the subjective score as the classification output means performing the classification task of 11 classes. Our sample number is not enough to ensure the classification accuracy of 11 classes. The classification error of the two FLPA calculation methods is 0.6690 ± 0.0512 and 0.7150 ± 0.0783, respectively. Therefore, we reduce the number of categories and divide the 11 score values into two classes to ensure classification accuracy. Scores greater than 5 are assigned positive labels, and the rest are assigned negative labels. This way is similar to a 2-point scale. Fewer categories mean more ambiguity in QoE description, but it can verify the feasibility of FLPA to measure QoE.

The results of SCC between the FLPA and the 2-point subjective score are shown in TABLE V. The FLPA of all rhythms at electrode pairs F3-F4 is significantly correlated with the subjective score, which is different from the results in TABLE IV. In addition, all the correlation coefficients in TABLE V are lower than those in TABLE IV for the same coordinates. However, the feature with the largest correlation coefficient is still F_{72}. The ranking result of FLPA feature importance is shown in Fig. 9. F_{72} is the most important feature, which is consistent with the results shown in Fig. 8. But the ranking of features after F_{72} has changed. The classification error of the two FLPA calculation methods in the two-classification is 0.2464 ± 0.0440 and 0.2688 ± 0.0476, respectively. According to the results of classification error of the 11-point scale and 2-point scale, the Logarithmic method is better than the Subtraction method.

Based on the above analysis, the F_{72} calculated Logarithmic may be the best indicator for evaluating QoE, which will be further verified by classification prediction.

D. Classification Prediction

Multiple classifiers are used to verify the performance of the selected metrics on the measured QoE. The accuracy of classification is calculated by the LOO cross-validation method.

To verify that F_{72} is more suitable than other features for QoE measurement, features ranked in the top 20% of importance, as well as features ranked in 20, 30, 40, 50, 60, and 70 are used for comparison. The classification results are shown in Fig. 10. It can be seen that among all the classification results, the maximum classification accuracy is obtained by the feature F_{72} and SVM classifier. The classification accuracy of KNN is 0.7135, which is the lowest classification accuracy among the four classifiers using F_{72}. The maximum classification accuracy represents the potential of the feature for classification, while the minimum classification accuracy represents the stability of the feature for classification. With these two properties as a reference, only the classification results of F_{62} are barely close to those of F_{72}. The classification results of the remaining features are obviously lower than those of F_{72}.

The number of features is gradually increased according to their importance order to further verify the performance of a single feature F_{72} in QoE evaluation. The classification results are shown in Fig. 11. The impact of increasing number of features on classification accuracy is a major concern. The classification accuracy of all classifiers fluctuates irregularly with the increase in the number of features. The classification accuracy is the highest when the number of features reaches 10 and then shows a downward trend. It may be that redundant features bring a lot of interference factors so increasing the number of features does not steadily improve the classification accuracy.

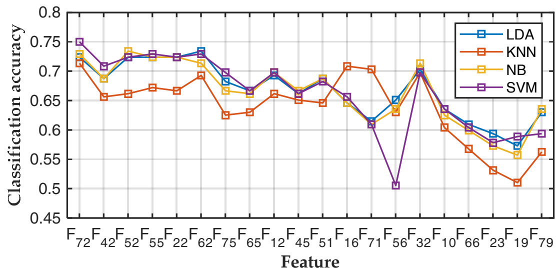

Fig. 10. Classification results using a single feature.

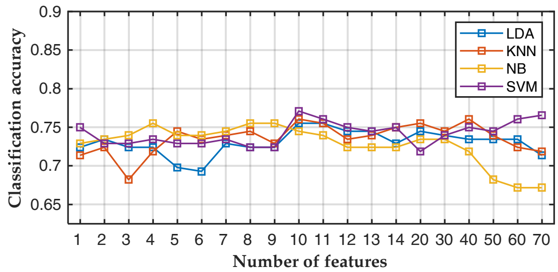

Fig. 11. Classification results using different numbers of features.

The classification accuracy using SVM and F_{72} can reach 0.75, which is slightly lower than the maximum classification accuracy of 0.77 in Fig. 11. If time cost is taken into account, we think the difference is tolerable. In other words, when using

TABLE V
THE RESULTS OF SCC BETWEEN FLPA AND SUBJECTIVE SCORES (2-POINT SCALE)

		Theta	Alpha	Beta	Gamma	TA	TAB	TABG	AB	ABG	BG
F3-F4	Sig. (2-tailed)	**3.888E-6**	**1.512E-8**	**9.258E-4**	**0.0131**	**5.442E-8**	**1.266E-5**	**0.0087**	**6.418E-5**	**0.0067**	**0.0026**
	Correlation	0.3262	0.3944	0.2372	0.1788	0.3800	0.3093	0.1889	0.2843	0.1949	0.2159
F5-F6	Sig. (2-tailed)	**2.171E-4**	**2.525E-8**	0.1580	0.7603	**3.639E-7**	**7.459E-9**	0.2704	**0.0022**	0.4245	0.4844
	Correlation	0.2639	0.3887	0.1023	0.0222	0.3573	0.2413	0.0799	0.2199	0.0580	0.0508
F7-F8	Sig. (2-tailed)	**2.104E-5**	**9.64E-10**	**2.608E-4**	**0.0040**	**3.537E-9**	**8.661E-7**	**0.0013**	**1.211E-6**	**0.0012**	**0.0013**
	Correlation	0.3018	0.4232	0.2607	0.2069	0.4099	0.3463	0.2305	0.3419	0.2320	0.2302
F3-F4 F5-F6	Sig. (2-tailed)	**7.700E-7**	**2.13E-12**	**0.0222**	0.5713	**9.84E-11**	**7.614E-6**	0.4140	**3.24E-5**	0.3249	0.3862
	Correlation	0.3478	0.4789	0.1650	0.0411	0.4452	0.3167	0.0593	0.2951	0.0714	0.0629
F3-F4 F7-F8	Sig. (2-tailed)	**6.719E-9**	**1.56E-13**	**6.418E-5**	**2.810E-4**	**4.08E-13**	**2.024E-8**	**8.102E-5**	**2.939E-8**	**1.055E-7**	**7.470E-5**
	Correlation	0.4040	0.4999	0.2843	0.2593	0.4923	0.3912	0.2805	0.3870	0.2762	0.2819
F5-F6 F7-F8	Sig. (2-tailed)	**3.252E-6**	**7.36E-13**	**0.0034**	0.0571	**1.85E-11**	**4.613E-8**	0.2050	**3.927E-7**	0.1460	**0.0197**
	Correlation	0.3287	0.4876	0.2103	0.1375	0.4603	0.3819	0.0919	0.3563	0.1053	0.1682
F3-F4 F5-F6 F7-F8	Sig. (2-tailed)	**2.130E-8**	**4.36E-16**	**0.0015**	**0.0345**	**1.03E-13**	**8.207E-9**	**0.0266**	**5.532E-8**	**0.0220**	**0.0104**
	Correlation	0.3906	0.5425	0.2281	0.1527	0.5031	0.4010	0.1601	0.3798	0.1652	0.1845

The bold number indicates p<0.05.

a single feature F_{72} for the classification task, we are 75% confident that our predictions are correct. Therefore, it is feasible to use FLPA features, especially F_{72}, to measure the QoE of VR with vibrotactile feedback.

V. Discussion

A. Interaction latency

In the user study, we make use of established commercial VR products to minimize any potential increase in interaction latency. Both audio-visual and haptic presentations are triggered by the controllers, with any additional delay being primarily attributed to the system. In general, when the interaction latency exceeds 20ms, the user will experience sensory conflict and even feel dizzy. Unfortunately, we lack the necessary experimental conditions to directly measure the overall device interaction latency. However, it is worth noting that none of the participants reported any feelings of delay or cybersickness in the questionnaire. Not receiving any feedback from users regarding the latency does not necessarily mean that there is no interaction latency. We can only conservatively assume that it does not have an obvious impact on our findings.

B. Classification Accuracy

EEG is a complex signal which is non-stationary and nonlinear. The acquisition and analysis of EEG data are easily disturbed by various factors. Due to the few relevant studies available for reference, we may not have reached the optimum in the selection of subjects, the design of experiments, and the method of classification. Under our best efforts, the classification accuracy of this paper is between 0.7 and 0.8. Referring to the results of references [21] and [22], we believe that the accuracy is within an acceptable range for the study of EEG signal analysis. The target information extracted from complex EEG signal still contains a lot of interfering noise. In the early stages of studying the use of EEG to measure the experience of VR with haptic feedback, we conservatively believe that the conclusions we have drawn are valuable for subsequent research on objective QoE evaluation.

C. Vibration and Motor Sensitivity of EEG

EEG is very movement-sensitive and even the slightest of vibrations can interfere with its readings. Vibration may further reduce the signal-to-noise ratio of EEG and increase the difficulty of extracting target information from EEG. However, vibration in this paper is not an interference factor, but a sensory information input mode in itself. The subjects avoided the movement of other limb parts to affect the EEG data by keeping their wrists still and so on. When the effects of vibration are confined to the hand, we believe that the recorded EEG containing vibration information is usable for subsequent data analysis.

D. Limitations

Subjective scoring is the measurement standard of QoE in this paper. The selection of subjects is one of the key links to ensure the validity and stability of experimental results, which is reflected in the accuracy of subjective scoring. Due to the Novel Coronavirus outbreak, subjects can only be recruited at Jilin University. They have the characteristics of concentrated age distribution and similar daily living habits. The influence of the limitations of the subject group on the experimental conclusion may require further discussion and analysis.

E. Future Directions

Due to the lack of theoretical research on tactile-related EEG, we study from the perspective of emotion. Among the many emotion-related EEG, FLPA is only studied in this paper. The use of more emotion-related EEG features may further improve the accuracy of predicting QoE. In addition, establishing a connection between tactile-related EEG and the QoE of tactile feedback in VR can help to understand the brain activity patterns associated with haptic perception.

VI. Conclusion

As an advanced application of multimedia, VR with haptic feedback will bring users an all-around multi-sensory immersive experience. However, there are still many problems to be studied in the concrete methods of QoE measurement. The QoE assessment of VR with haptic feedback is highly dependent on subjective measurements. Inspired by the fact that physiological signals can reflect the user's mental state, this paper uses EEG-driven physiological measurements to evaluate the QoE of VR with vibrotactile feedback. In our research on VR experience with vibrotactile feedback, we find that different vibration stimuli evoke different FLPA phenomena. FLPA can reflect the user's emotional state, and emotion is a psychological measurement of QoE. Therefore, it is reasonable to use FLPA to measure QoE. SCC is used to screen out FLPA features that are not significantly related to the subjective score of QoE. Then RF is used to rank the importance of FLPA features and select the best indicator F_{72}. The prediction accuracy of the SVM classifier trained with a one-dimensional feature F_{72} can reach 0.75, which verifies the feasibility of FLPA as a physiological indicator to measure QoE. In this paper, we carry out exploratory work on objective measurement methods of QoE for VR with vibrotactile feedback and achieve mutual interpretation of EEG-based physiological measurements and subjective cognitive outcomes of QoE. The specific promotion and application of the conclusions of this paper in VR remain to be studied.

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Yan Zhang received an M.S. degree from Jilin University, Changchun, China, in 2018. He is currently a Ph.D. student in information and communication engineering, Jilin University, Changchun, China. His research interests include human-computer interaction and signal processing.

Yuning Su earned his Bachelor's degree from Jilin University in Changchun, China, in 2019. He is now pursuing his Ph.D. in Computing Science at Simon Fraser University in British Columbia, Canada. Yuning's primary research areas are interactive materials and haptic rendering.

Xiaoying Sun received a Ph.D. degree in communication and information systems from Jilin University, Changchun, China, in 2005. Currently, he is a professor at Jilin University, Changchun, China. His research interests include tactile representation, human-computer interaction, and signal processing.