Neurophysiological and Subjective Analysis of VR Emotion Induction Paradigm

Ming Li, Junjun Pan, Yang Gao*, Yang Shen, Fang Luo, Ju Dai, Aimin Hao and Hong Qin

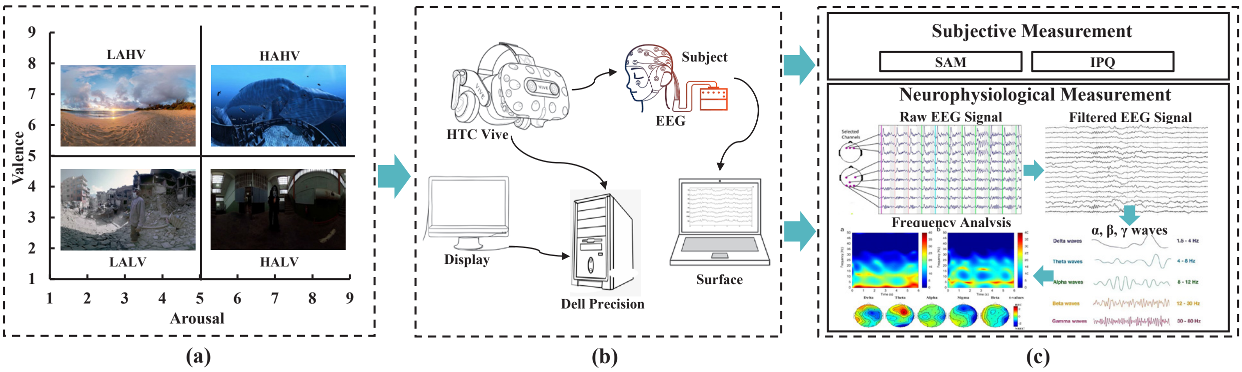


Fig. 1. An overview of our framework for VR emotion induction and analysis. (a): The expected emotional state and emotion induction materials; (b): The experiment set-up; (c): The subjective and neurophysiological data process and analysis.

Abstract—The ecological validity of emotion-inducing scenarios is essential for emotion research. In contrast to the classical passive induction paradigm, immersive VR fully engages the psychological and physiological components of the subject, which is considered an ecologically valid paradigm for studying emotion. Several studies investigate the emotional responses to different VR tasks or games using subjective scales. However, little research regards VR as an eliciting material, especially when systematically analyzing emotional processes in VR from a neurophysiological perspective. To fill this gap and scientifically evaluate VR's ability to be used as an active method for emotion elicitation, we investigate the dynamic relationship between explicit information (subjective evaluations) and implicit information (objective neurophysiological data). A total of 28 participants are enlisted to watch eight VR videos while their SAM/IPQ scores and EEG data are recorded simultaneously. In ecologically valid scenarios, the subjective results demonstrate that VR has significant advantages for evoking emotion in arousal-valence. This conclusion is backed by our examination of objective neurophysiological evidence that VR videos effectively induce high-arousal emotions. In addition, we obtain features of critical channels and frequency oscillations associated with emotional valence, thereby validating previous research in more lifelike circumstances. In particular, we discover hemispheric asymmetry in the occipital region under high and low emotional arousal, which adds to our understanding of neural features and the dynamics of emotional arousal. As a result, we successfully integrate EEG and VR to demonstrate that VR is more pragmatic for evoking natural feelings and is beneficial for emotional research. Our research has set a precedent for new methodologies of using VR induction paradigms to acquire a more reliable explanation of affective computing.

Index Terms—Emotion induction, Virtual Reality, Neurophysiological analysis, Electroencephalogram

1 Introduction

A widely held belief in psychology is that an emotional episode involves simultaneous changes in multiple psychological and physiological components [1]. Specific qualitative emotional states (excitement, fear, depression, etc.) are defined by particular changes in six emotional components: cognitive, motivation, physiological, behavioral, experiential (feeling), and a regulation component [2]. Appraisal theory is an emotion-based causation theory based on the emotional components and has been highlighted for its importance in the emotion framework by previous studies [3, 4]. According to this theory, the cognitive component is the primary driver of changes in the other emotional components. When confronted with a situation, one should first assess the issue before making the psychological and physiological changes [5]. Classic emotion-induction paradigms (such as watching pictures/videos or listening to music), on the other hand, rely on passive emotion induction in the laboratory, which has a large gap with real-world scenarios and can not fully engage the psychological and physiological components of the subject [6]. These paradigms do not entirely adhere to appraisal theory and lack ecological validity. As a result, eliciting strong and multi-component emotions is difficult, impeding understanding of emotional processes. An ideal emotional induction paradigm would immerse subjects in a more dynamic and realistic environment that could be modified based on their appraisal while engaging psychological and physiological subsystems more meaningfully. VR is one potential medium that fits these requirements and remedies the gap between the laboratory and real-world environments.

As an emerging technology, VR can provide complex virtual environments with high immersion and realism while allowing for experimental control. It immerses the user entirely into the created en-

*Corresponding author, gaoyangvr@buaa.edu.cn.

- *Ming Li is with State Key Laboratory of Virtual Reality Technology and Systems, Beihang University, Beijing, China.*
- *Junjun Pan, Yang Gao and Aimin Hao are with State Key Laboratory of Virtual Reality Technology and Systems, and also with Beijing Advanced Innovation Center for Biomedical Engineering, Beihang University, Beijing, China. They are also with the Research Unit of Virtual Body and Virtual Surgery Technologies, Chinese Academy of Medical Sciences, 2019RU004, Beijing, China. Junjun Pan, Ju Dai, and Aimin Hao are also with Peng Cheng Laboratory, Shenzhen, China.*
- *Yang Shen and Fang Luo are with School of psychology, Beijing Normal University, Beijing, China.*
- *Hong Qin is with Department of Computer Science, Stony Brook University, Stony Brook, NY 11794 USA.*

Manuscript received 11 March 2022; revised 11 June 2022; accepted 2 July 2022. Date of publication 01 September 2022; date of current version 03 October 2022. Digital Object Identifier no. 10.1109/TVCG.2022.3203099

vironment, potentially enhancing the user's emotional experience [7]. In a virtual environment, emotions can be evoked more naturally and realistically [8]. The combination of VR and emotions is beneficial in the fields of entertainment, education, and psychotherapy [9]. Due to its relatively high ecological and construct validity, VR could be a good solution to the emotional induction paradigm.

By analyzing subjective scales, current researches show that VR can change users' emotional responses [10]. However, most of these studies concentrate on the emotional effects of various VR tasks or games. There have been few studies regarding VR as an eliciting material due to the rarity of VR-based emotion-evoking materials, especially the scarcity of using objective neurophysiological data to study emotional processes in VR systematically. It is worth objectively exploring the ability of VR as an emotion-inducing material by investigating the relationship between explicit information (arousal and valence ratings) and implicit information (features of neurophysiological signals corresponding to arousal/valence). On the other hand, previous studies have shown the variety of physiological signals and subjective scales under different emotions [11,12]. Both neurophysiological signals and subjective scale ratings are important for emotion evaluation. Uncovering the connection between these two data types is essential for understanding the different emotional states reflected by neurophysiological signals.

In this paper, we aim to explore the great potential of the VR emotion induction paradigm by analyzing the dynamic relationship between subjective and objective data obtained throughout participants' VR movie watching experiences. For subjective data, we adopt the Self-assessment Manekin (SAM) and Igroup Presence Questionnaire (IPQ) to measure participants' emotional feelings and presence in a virtual environment. EEG data is collected as objective information because it intuitively reflects an individual's emotional activity [13]. The EEG analysis enables us to provide an objective and accurate explanation of users' varied emotional fluctuations from a neurophysiological perspective. Furthermore, we decode the brain regions and EEG features related to emotional arousal by leveraging the high ecological validity of immersive VR with the goal of learning more about the association between emotional arousal and specific brain regions, specifically filling the gap between hemispheric asymmetry and emotional arousal. This can provide improved brain models and extend prior findings [14] on the neurophysiology of emotion toward real-world scenarios and applications. The contributions of this study are as follows:

- We set a precedent by using VR videos to investigate the EEG features of diverse emotional states systematically, demonstrating the potential power of VR as stimulus material for emotion research from a neurophysiological perspective.

- We discover the crucial brain regions and frequency oscillations associated with emotional valence and arousal. This finding inherits previous conclusions and verifies them in naturalistic environments. It is, thereby, a critical step to extend emotion research towards real-world neuroscience.

- Due to the unique properties of immersive VR of inducing high-arousal emotions, we find there is hemispheric lateralization of α waves in occipital regions for high-arousal emotions, which can be a valuable study and bring new insights for emotional arousal in affective computing.

2 Related Works

We begin by discussing existing research on classic emotion induction paradigms and the issues that motivated our research. Then we investigate the advantages of VR and explain why it is expected to become a fundamental tool for emotion research. Finally, we go through the history of neurophysiological signals as well as the present status of emotion induction research in an immersive VR environment.

2.1 Classic Emotion Induction Paradigms

An effective emotion induction paradigm could produce the subject's intended emotional states, which is crucial for studying emotion processes. According to the experimental environment, emotion induction paradigms can be divided into the field or laboratory. According to the induction scenarios, they can also be divided into active (the subject actively engages in the emotion induction scenario) or passive (the subject passively faces various emotion induction stimuli). Up to now, passive emotion induction in the laboratory has been widely used [15]. According to the presentation of sensory channels, the selected emotion induction materials can be classified into visual, auditory, olfactory, and multi-channel stimuli. Visual stimuli are the most commonly used method, presenting emotionally colored text or pictures to the subjects [16]. By far, the National Institute of Mental Health (NIMH) has established relatively complete libraries of standard stimulus materials, such as Affective Norms for English Text (ANET) [17] and the International Affective Picture System (IAPS) [18]. NIMH has also established International Affective Digital Sounds (IADS) for auditory stimulation. Multi-channel stimulus generally refers to video clips such as music videos and short videos. It combines a variety of induction materials and has become one of the most popular induction methods [19]. Researchers have published some affective databases such as DEAP, MAHNOB-HCI, SEED, AMIGOS, and ASCERTAIN [6,14,19–22]. These paradigms have some specific benefits. Experimenters can strictly control the presentation of stimulus materials and the experimental environment while measuring multimodal data (such as physiological signals and facial expressions).

However, in the laboratory, the passive emotion induction paradigm does not fully incorporate the component definition of emotion and appraisal theory. The underlying neurophysiological mechanism of this paradigm is the mirror-neuron mechanism. When observing another's activities, a person's brain will also perform similar actions, and emotion induction should be based on this principle. Therefore, rather than an appraisal theory, the underlying causal model of the classic emotion induction paradigm could be understood as the "contagion" of emotion. This is not a widely accepted theory of emotional causality [23]. Meanwhile, due to the passive form of the task, the subject's psychological and physiological subsystems cannot be fully mobilized. Because it makes no sense to run away or avoid scary pictures on computer 2D displays, the motive and behavioral components of emotion lose meaning. To this end, some studies have found that subjects participate more actively in video game scenarios, but the subject and the scenario are still separated by the screen [24]. As a result, subjects are frequently observers rather than participants, expressing their emotional reactions through game avatars. To summarize, the classic emotion induction paradigm lacks sufficient "ecological validity", resulting in a lackluster emotional response.

2.2 VR Emotion Induction Paradigms

Unlike the classic emotional induction paradigm mentioned above, VR could provide ecological validity scenarios that fully engage the psychological and physiological components of the subject. Furthermore, the subject and virtual scenarios will not be separated by the screen and virtual avatar. The user can be completely immersed in a virtual scenario and feel as if they are "there". Therefore, VR is considered an effective measurement with a high level of ecological and structural validity.

Among the current limited emotional science research, VR scenarios are mostly used for psychotherapy. For example, psychologists frequently used "exposure therapy" to expose patients to situations that make them feel anxious in order to reduce fear responses or anxiety through repeated exposure [25,26]. Some studies concentrated on how virtual humans with different rendering styles or facial expressions affect the user's emotional state [27]. Although a few studies combined VR scenarios with emotions, they do not refer to VR as an emotion elicitation material. Cao et al. [28] generated three types of virtual environments (i.e., interior, street, and park), each with three different emotions (i.e., negative, neutral, and positive) induced by different sounds and lighting effects. The researchers then compared the cognitive activities of participants in a non-CVR (i.e., 2D monitor) and a CVR (i.e., 3D monitor) environment (i.e., head-mounted display). However, this study only explored the effects of different emotions on cognitive activity in VR, not the changes in EEG features. Furthermore, it only looked at general positive and negative emotions rather than studying the mechanism of emotion generation by following the framework of emotions. There are also studies investigating how the amount of interaction affects the sense of presence in the natural environment, as well as its effect on arousal and valence of emotion [29]. However, this work only used VR horror games to induce fear emotions (high arousal and low valence), so the effectiveness of VR in eliciting other emotions was not tested. In addition, these studies only used subjective questionnaires to evaluate the effects of emotion induction. The subjects have a hard time describing their emotions accurately and quantitatively. Moreover, some subjects have no experience with self-description of emotions during their first experiment. In fact, an important challenge in psychology and clinical research related to emotions is how to find an accurate and objective method for labeling emotion categories. Objective neurophysiological data, such as EEG and electrocardiogram (ECG), which are not easy to disguise and contain more information, can better reflect a person's actual emotional state objectively and are gradually applied in emotion research. However, very few VR emotional studies used neurophysiological data to measure emotions, which limits our understanding of how emotions work.

2.3 Neurophysiological of Emotion

EEG signals are primarily derived from brain neuron firing activities, which can be detected on the scalp by sophisticated collection equipment. Due to its high time resolution and strong functional specificity, it has been valued by researchers and applied in VR in recent years [30, 31]. There are five frequency bands in the EEG signal: δ (1-4Hz), θ (4-7Hz), α(8-12Hz), β (13-28Hz), and γ (29-50Hz). Each band corresponds to a different frequency that reflects different activity states of the brain. Meanwhile, because emotion generation is closely linked to various areas of the brain, changes in emotional state can be monitored and analyzed by collecting EEG [32, 33]. A previous study found that the central α power is inversely related to arousal [34]. For the low-frequencies, θ and α bands in the occipital region, the increase in valence leads to an increase in power. Also, hemispherical asymmetry in the frontal lobe region is highly relevant to valence and other emotional states. [35–38]. In addition, researchers focused on stable emotional patterns that do not change over time [39]. They discovered that the activation level of the temporal lobe region for positive emotions is much higher in the β and γ frequency bands than for negative emotions. The neural pattern of normal emotions has a more obvious α-band response in the occipital and parietal regions. The neural pattern of negative emotions has a more obvious δ-band response in the parietal and occipital lobe regions and a higher γ-band response in the frontal lobe.

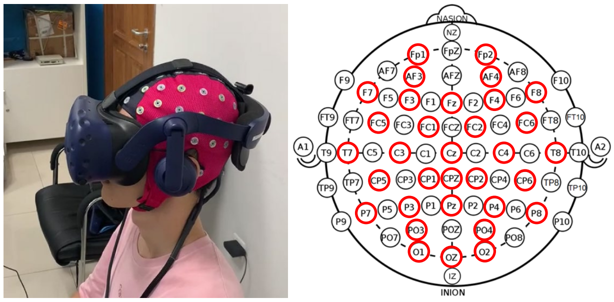
According to the findings of the prior studies, the features of each EEG band are closely related to various emotional states. However, most current researches explored the effects of different tasks in VR on the EEG. None of them conducted a systematic study of the changes in EEG during VR experiences under different emotions. It is a challenging but significant task to extract specific EEG features as evaluation indicators to quantify emotional changes during the VR experiences.

3 Methods

We devise a within-subjects experiment to compare EEG features in specific bands and subjective ratings under various emotional conditions. We use EEG to investigate the emotional induction effect of VR videos on the neurophysiological level, as well as to collect subjective questionnaire scores while the subjects are watching VR videos. Fig.1 depicts an overview of the VR emotion induction and analysis of our experiment. In this section, we will go over the experiment in great detail.

3.1 Participants and Ethics

The recordings are made in a temperature-controlled laboratory setting. This study includes 28 healthy volunteers aged 21 to 33 (M = 24.23, SD = 4.15, 16 males and 12 females) with normal hearing, vision, and mental health. All of the volunteers are college students with no history of heart disease, neurological disease, or other emotionally-related diseases. This investigation has been approved by the local ethics committee.



(a) (b)

Fig. 2. EEG equipment and HMD used in our study. (a) is the subject wearing both an EEG cap and an HTC Vive VR headset. (b) is the EEG electrodes configuration for the current study. The red circles indicate the channels we used.

3.2 Experiment Apparatus

Our experimental equipment consists of the following parts: a computer (Intel Core i7 processor, GTX 2060 graphics card, and 16 GB RAM), an HTC Vive Pro HMD for displaying VR videos. Each participant's interpupillary distance is measured and set. EEG signals are collected by ANT Neuro equipment, which has a CE certificate as a medical device and includes a cap with 64 electrodes. Electrode placement follows the 10/20 system. Besides, to prevent the HMD from exerting pressure on the front-central electrodes, a lateral elastic band is used to fix the HMD while the upper elastic band is loose. In order to compare with the conclusions of previous research, we use the same electrode configuration with a total of 32 EEG channels. It agrees with two well-known emotion studies: the DEAP and MAHNOB-HCI datasets. The EEG electrodes configuration and HMD are shown in Fig. 2. All electrodes are referenced to CPz and grounded to the forehead. In order to ensure the quality of EEG signals, we fill the electrodes on the cap with non-abrasive gel, and the electrode impedance should be less than $5k\Omega$ during the experiment.

3.3 Stimuli Selection

Due to the lack of necessary expertise, unavailability of gold standard equipment, and proper controllable environment, there is rarely appropriate VR-based material on affective computing [40]. Therefore, the stimulus used in our experiment is selected from a Stanford immersive VR video public database [41]. The dataset, which includes 73 immersive VR clips, is currently the only public VR video dataset available. Each video has a valence and arousal score that is distributed in the Russell arousal-valence model's four quadrants [42]. The four quadrants in this arousal-valence plane (AV plane) are low arousal/low valence (LALV), low arousal/high valence (LAHV), high arousal/low valence (HALV), and high arousal/high valence (HAHV). For the LAHV and LALV quadrants, we choose two videos with the scores closest to the extreme corner of the quadrant, respectively. Due to the lack of high arousal and low valence videos in this dataset, we select 15 horror videos with the highest view count from YouTube. Each video has been rated on a discrete 9-point scale for valence and arousal by at least 16 volunteers. For each video x, we calculate the normalized arousal and valence scores by dividing the average score with the standard deviation (μ_x/σ_x). We also select two videos close to the extreme corner of the quadrant on the AV plane. The high arousal and low valence videos applied in this paper are available online [1], [2]. In addition, for the video of the HAHV quadrant, titled speed flying and tightrope walking, all subjects consider that the video would cause severe cybersickness, which may have a significant impact on EEG power [43]. Therefore, to eliminate cybersickness in the experiment, we choose The Blu–Whale Encounter, a VR game available on Vive's Steam platform. This game

[1]https://www.youtube.com/watch?v=ViLReDIvk_A
[2]https://www.youtube.com/watch?v=C0Rl4m38gOU

Fig. 3. Sample screenshots of participants and VR videos with different emotions they watched: The emotions corresponding to the four columns are LALV, HALV, LAHV, and HAHV. Each column from top to bottom is the Nepal Earthquake Aftermath, the Earthquake Site, the Real Run, the Conjuring 2, the Malaekahana Sunrise, the Mountain Stillness, the Whale Encounter, and the Reef Migration.

is more like a movie-watching experience, as it is relatively passive and straightforward. It has been proven to induce high arousal and valence induction while also providing players with a vivid first impression of VR [44]. It contains three fragments, and we choose two of them as stimulus materials. In the end, as shown in Fig.3, we select eight VR videos, each with a distinct title, video screenshot, and its corresponding quadrant.

3.4 Measurements

We have measured and compared these two types of data to quantify and verify the effectiveness of VR videos as emotion elicitation materials. For subjective data, we adopt the 9-point SAM scale, which is widely used to measure the valence, arousal, and dominance associated with a person's affective reaction [45]. The valence scale ranges from unhappy to happy, and the arousal scale ranges from calm to excitement. The level of dominance varies from submissive ("out of control) to dominant ("in control"). In addition, since presence has been proved to be an essential factor in emotional induction and is the core psychological structure that describes the VR experience, we also record IPQ scores to measure the sense of presence experienced in a virtual environment [46]. It consists of 14 items, which can measure users' spatial presence, involvement, and sense of realness.

For neurophysiological data, EEG includes time series of multiple channels, which correspond to the measured values of different positions in the cerebral cortex. However, noises such as body movements, VR displays, electrooculography (EOG), ECG, and electromyography (EMG) can easily interfere with EEG signals [47]. To reduce the possible interference caused by body movements, external noises, and equipment discomfort, we instruct the subjects not to move their bodies and heads as much as possible when viewing VR videos. Although this may limit the subject's experience to some degree, subjects remain in a virtual environment isolated from the outside world, are not disturbed by other people or noises. They can concentrate on the emotion induction experiment. In addition, to obtain clean and high-quality EEG signals for frequency-domain feature extraction, we adopt EEGLAB for physiological signal processing. EEGLAB is an open-source Matlab toolbox that provides powerful algorithms for EEG preprocessing, feature extraction, and emotion recognition [48]. Specifically, we adopt the following steps in our experiments: First, we use a high sampling frequency of 512Hz to acquire raw EEG data, which can filter out the interference caused by monitors (50Hz to 60Hz) and VR HMDs (90Hz). Then, the signal is resampled to 128Hz (via the 'pop_resample.m' method in EEGLAB) and re-referenced to the linked papillae (electrodes M1 and M2). Second, the signal is filtered with a band-pass from 4 to 47Hz to minimize the introduction of artifacts(via FIR filter in EEGLAB). Third, a visual inspection is conducted to remove abnormal signals with amplitudes beyond ±100 (μv), since signals with such large amplitudes are no longer caused by cognitive activity. Fourth, we adopt Independent Component Analysis (ICA), a blind source separation (BSS) based method, to remove artifacts while retaining as much information as possible. We decompose the entire EEG signal set into 32 independent components (ICs). These ICs are determined as artifacts or neural activity components related to emotion by a semi-automatic method using the SASICA software in EEGLAB and visual inspection by experts [49]. Finally, we remove an average of 9.37 components per subject and obtain pure EEG signals for the following feature extraction step.

Table 1. 14 pairs of hemispheric asymmetry electrodes used in our experiment.

Pair No.	1	2	3	4	5	6	7
Left	Fp1	AF3	F7	F3	FC5	FC1	T7
Right	Fp2	AF4	F8	F4	FC6	FC2	T8
Pair No.	8	9	10	11	12	13	14
Left	C3	CP5	CP1	P7	P3	PO3	O1
Right	C4	CP6	CP2	P8	P4	PO4	O2

Since the most significant feature related to emotion usually exists in the frequency domain, and different frequency bands can reflect different brain activities [50]. We focus on extracting and comparing the frequency domain features of EEG signals under different emotions, including Power Spectral Density (PSD) and Hemispherical Asymmetry. The PSD defines how the power of a signal is distributed over frequency and is widely used in the field of emotion recognition [51]. In this paper, for θ, α, β, and γ bands, the PSD is calculated using Welch's method in Python-MNE. The welch method allows data segments to overlap and thus the variance characteristics can be well improved. The overlapping of segmented data reduces the irrelevance of each segment [52]. Specifically, the signal is first divided into n segments that allow overlapping, then each segment of data is windowed before computing the PSD and finally calculated the PSD average of multiple-segmented data. We use a Hanning window of 256 samples with an overlap of 128 samples. Hanning window can improve spectral distortion caused by the rectangular window [53]. Besides, to minimize stimulus-unrelated power over time, we perform a baseline correction. We use the fixed stage of five seconds before each video as the baseline, and the power of the baseline stage is subtracted from the power of the trial. Finally, these PSD values are averaged over the θ (4 - 7 Hz), α (7 - 13 Hz), β (14 - 29 Hz), and γ (30 - 47 Hz) bands, as the EEG power used in this research. We also calculate the differences between the PSDs of 14 pairs of hemispheric asymmetry electrodes. The details of the 14 pairs of electrodes are shown in Tab. 1.

3.5 Experimental Setup

All subjects voluntarily took part in the study and were carefully informed about the objectives, experimental procedures, and risks. Each participant was required to refrain from regular medication, alcohol, or caffeine the day before the experiment and refrain from strenuous physical activity for 48 hours before the test sessions. Before experiments,

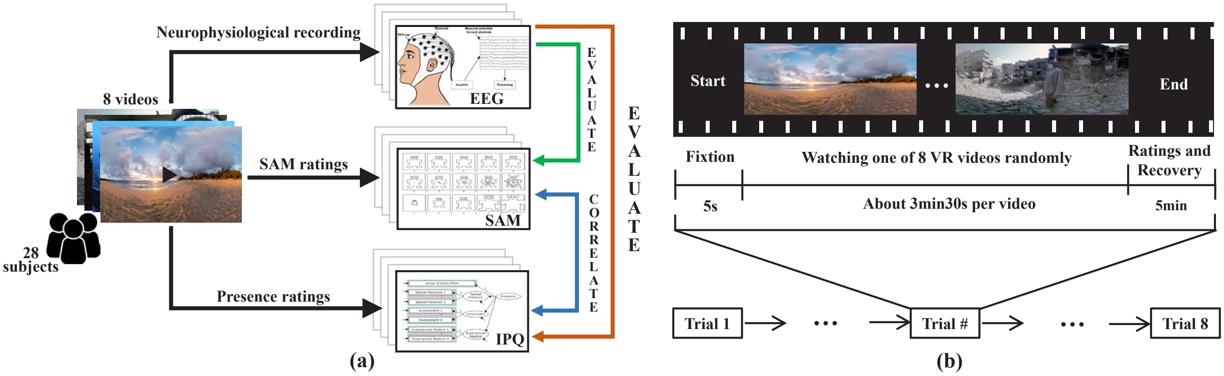


Fig. 4. (a) The study overview in our experiment. (b) Experiment process for each trial.

volunteers subscribed to a written informed consent form. They were also told that they could stop at any time without any consequences. Meanwhile, the experimenter explains the emotion scales used and how to fill in the self-assessment form. Next, an EEG cap was placed and checked the quality of signals. Finally, the experimenter left the room and started recording.

One baseline stage and eight trials make up the experiment. After the experiment began, the subjects were instructed to sit quietly in the chair for five minutes. Additionally, the subject's SAM score was recorded as a baseline measurement. The eight VR videos were then shown in eight trials in random order. Each trial consists of three steps. A fixation cross was displayed for the first five seconds. The participants were then assigned to watch one of eight virtual reality videos at random. After watching each video, they were asked to rate their emotions and sense of presence using the SAM and IPQ questionnaires. To avoid the pressure artifacts of wearing the VR HMD repeatedly and disturbing the position of the EEG electrodes, the SAM and IPQ questionnaires are displayed on a virtual screen. This allows subjects to fill out the questionnaire without removing the VR HMD. It takes about five minutes to complete the rating and recovery process. Subjects can also recover from the previous emotion-induced stage during this period to avoid mental fatigue. Furthermore, the videos should be selectively crafted to reduce the discomfort caused by wearing the VR device while effectively eliciting the desired emotion. As a result, each VR video is about three minutes and thirty seconds long. The experiment takes about an hour to complete. The study overview and experimental process of each trial are shown in Fig. 4.

3.6 Statistical Analysis

All analyses are conducted at a 0.05 level of significance. The normality of all data is tested using the Shapiro-Wilk test. We use non-parametric Wilcoxon signed-rank tests to check if the arousal ratings of video stimuli induced different valence ratings, also with the statistical differences of presence under different emotional conditions. A paired-samples t-test is used to compare the EEG power of θ, α, β, and γ bands between high-arousal/low-arousal or high-valence/low-valence emotions. Due to the small sample scale, we conduct the two-way repeated measures ANOVA to investigate the hemisphere asymmetry effect, with two within-group factors of emotion (high-arousal/low-arousal or high-valence/low-valence) and hemisphere (left/right) for EEG power. We also perform simple main effects analysis if any interaction among factors was found. Greenhouse-Geisser is used to correct the degrees of freedom if the assumption of sphericity is violated by Mauchly's spherical test. Multiple comparisons are corrected with the Bonferroni correction. All statistical analyses are conducted using SPSS 22.0.

4 Results

This section shows the results of subjective scale and neurophysiological analysis.

4.1 Analysis of Subjective SAM Ratings

We list the average ratings of participants' arousal, valence, and dominance in response to eight video stimuli over the AV plane. As shown in Fig.5, the Nepal Earthquake Aftermath (M=4.4, SD=2.1 for A; M=3.1, SD=1.3 for V; M=5.4, SD=1.6 for D) and the Earthquake Site (M=4.8, SD=1.8 for A; M=3.2, SD=0.7 for V; M=5.4, SD=1.4 for D) belong to the LALV quadrant. The Real Run (M=8.0, SD=2.7 for A; M=2.3, SD=0.3 for V; M=3.8, SD=1.2 for D) and the Conjuring 2 (M=8.2, SD=1.9 for A; M=2.0, SD=0.3 for V; M=3.5, SD=1.0 for D) belong to the HALV quadrant. The Malaekahana Sunrise (M=4.1, SD=1.3 for A; M=6.7, SD=1.7 for V; M=7.0, SD=2.3 for D) and the Mountain Stillness (M=4.0, SD=0.9 for A; M=6.8, SD=2.1 for V; M=6.6, SD=2.0 for D) belong to the LAHV quadrant. The Whale Encounter (M=7.4, SD=2.5 for A; M=6.6, SD=1.7 for V; M=5.4, SD=1.1 for D) and the Reef Migration (M=7.2, SD=1.6 for A; M=7.8, SD=2.1 for V; M=6.5, SD=1.3 for D) belong to the HAHV quadrant.

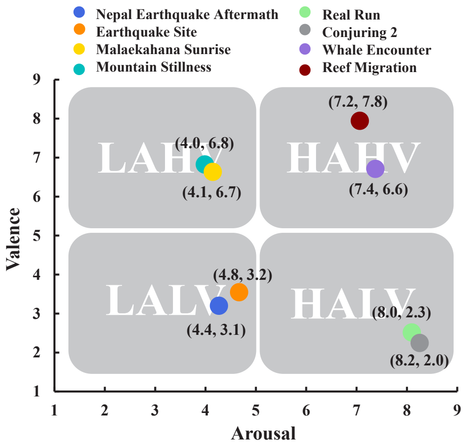


Fig. 5. The distribution of 8 VR videos in the valance-arousal plane.

Participants may confuse these three scales as a result of their habits or when they are tired. To analyze the inter-correlation between the three scales of valence, arousal, and dominance, we calculate Pearson correlation coefficients of them. As we can see from Tab. 2, the results show a strong positive correlation between dominance and valence. However, the correlation between valence and arousal is very weak.

Due to the non-normality of the data revealed by the Shapiro-Wilk test, we perform the non-parametric Wilcoxon signed-rank tests to verify that the subjects can distinguish the emotions of the four quadrants well. Because each quadrant has two videos, we draw the average SAM ratings of a pair of videos for each quadrant. As shown in Fig. 7, the results show that valence ratings differed very significantly for HA video stimuli ($p < 0.001$), also differed very significantly for LA video stimuli ($p < 0.001$). Conversely, we find arousal ratings differed very

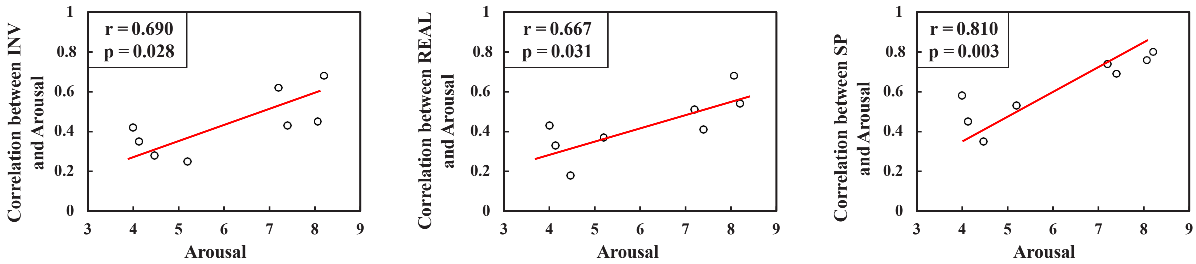


Fig. 6. The correlation between the global arousal score of eight videos and the correlation between presence and arousal of videos.

Table 2. The inter-correlation between three scales of valence, arousal, and dominance (* = $p < 0.05$).

Scale	Valence	Arousal	Dominance
Valence	1	0.12	0.43*
Arousal		1	0.19
Dominance			1

significantly for HV video stimuli ($p < 0.001$), also differed significantly for LA video stimuli ($p < 0.01$). For dominance rating, the results show that there is a significant difference between LV and HV video stimuli ($p < 0.001$). In particular, emotion induction worked quite successfully for high arousal conditions, with the corresponding valence ratings distributed in two extremes (2.2 for HALV and 7.23 for HAHV, respectively).

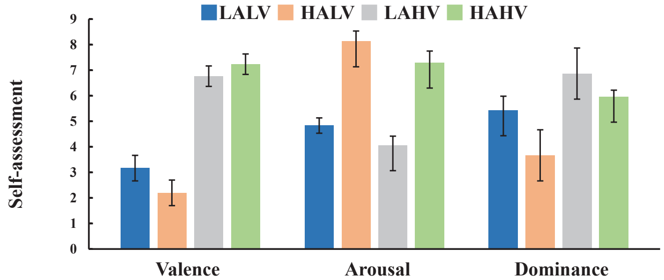


Fig. 7. The mean ratings of participants for valence, arousal, and dominance for the emotion of the four quadrants (LALV, HALV, LAHV, HAHV). The rating is averaged per subject and per condition.

4.2 Analysis of Subjective IPQ Ratings

We then analyze the statistical differences of presence under different emotional conditions. We use the non-parametric Wilcoxon signed-rank tests due to the non-normality of the data revealed by the Shapiro-Wilk test. As shown in Fig.8, there are significant differences in the IPQ ratings for involvement, sense of realism, and spatial presence between high arousal/low arousal. Specifically, HA video stimuli has significantly higher involvement ($p < 0.01$), sense of realism ($p < 0.01$), and spatial presence ($p < 0.05$) compared with LA video stimuli. In addition, we find no significant differences in these three scales between HV and LV.

4.3 The Relationship between Presence and Arousal

To explain the mechanism behind VR-induced high-arousal emotions, we analyze the correlation between SP, INV, REAL, valence, and arousal ratings of eight videos in this section. We calculate the average of five ratings from 28 subjects for each video. Then, the Pearson correlation coefficients of the average rating of eight videos are calculated. The result is shown in Tab. 3, there is no significant correlation among valence and INV ($r = -0.143$), REAL ($r = -0.167$) and SP ($r = -0.395$). However, a strong linear relationship exists between arousal and INV ($r = 0.619$), REAL ($r = 0.643$), SP ($r = 0.826$).

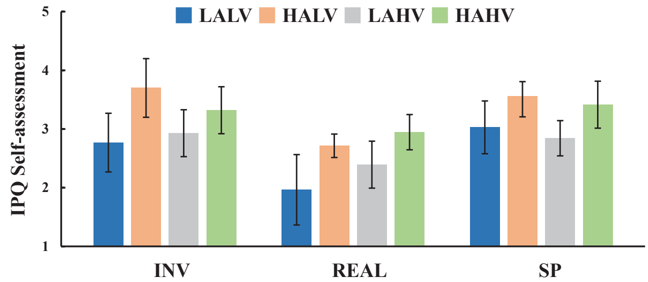


Fig. 8. The mean ratings of subjects for involvement (INV), sense of realness (REAL), and spatial presence (SP) for the emotion of the four quadrants (LALV, HALV, LAHV, HAHV). The rating is averaged per subject and per condition.

Table 3. Correlation coefficients between the mean ratings of participants for INV, REAL, SP, Valence and Arousal (* = $p < 0.05$).

Scale	INV	REAL	SP
Valence	-0.143	-0.167	-0.395
Arousal	0.619*	0.643*	0.826*

We also calculate the Pearson correlation coefficient between arousal and presence ratings of 28 subjects for each video. We obtain eight correlation coefficients for a total of eight videos. Then, we calculate the correlation between the average arousal ratings of eight VR videos and the correlation between the presence and arousal of videos. As shown in Fig.6, for each video, the arousal scores rise with an increasing correlation coefficient between arousal and INV ($r = 0.690$, $p = 0.028$), REAL ($r = 0.667$, $p = 0.031$), SP ($r = 0.810$, $p = 0.003$), respectively.

4.4 Analysis of EEG Power Under Different Emotional States

The EEG power of θ, α, β, and γ for each channel are calculated for all subjects under high-arousal and low-arousal emotions. The Shapiro-Wilk test indicates the data are normally distributed, so we use the pair t-tests to compare the power between different emotions. As shown in Fig. 9, for the θ band, low-arousal emotions have a higher power in the prefrontal lobe than high-arousal one. The occipital and parietal lobe activate more for low-arousal emotions than high-arousal emotions in the α band. Low-arousal emotions in β band have a higher power in the right lateral temporal lobe than high-arousal emotions. In addition, the difference between the two emotions for the γ band is not found. Specifically, we list and discuss the channels with significant differences, as shown in Tab. 4. For the θ band, the paired-samples t-test results show that significant differences are found for AF4 ($p < 0.01$) between HA ($M = -0.55$, $SD = 0.34$) and LA ($M = 0.65$, $SD = 0.42$), FP2 ($p < 0.01$) between HA ($M = -0.17$, $SD = 0.09$) and LA ($M = 0.34$, $SD = 0.12$), also exist for F4 ($p < 0.01$) between HA ($M =$

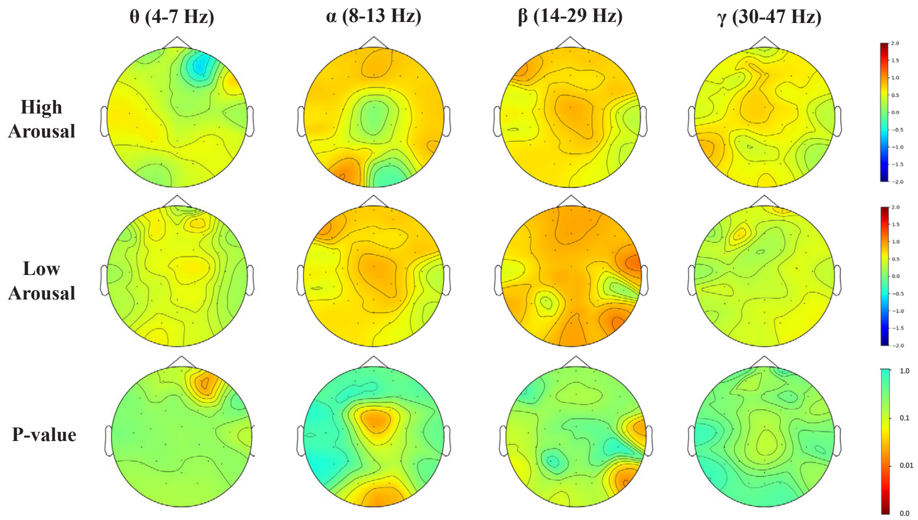


Fig. 9. The EEG power of θ (4-7Hz), α (8-13Hz), β (14-29Hz), and γ (30-47Hz) over all subjects for high-arousal and low-arousal.

-0.43, SD = 0.28) and LA (M = 0.51, SD = 0.32). For the α band, we find significant differences for Cz ($p < 0.01$) between HA (M = 0.07, SD = 0.12) and LA (M = 0.87, SD = 0.45), FC1 ($p < 0.05$) between HA (M = 0.59, SD = 0.33) and LA (M = 0.75, SD = 0.23), FC2 ($p < 0.05$) between HA (M = 0.55, SD = 0.23) and LA (M = 0.71, SD = 0.41), Oz ($p < 0.05$) between HA (M = 0.54, SD = 0.11) and LA (M = 0.64, SD = 0.39), O1 ($p < 0.05$) between HA (M = 0.81, SD = 0.36) and LA (M = 0.67, SD = 0.33), also exist for O2 ($p < 0.01$) between HA (M = 0.25, SD = 0.18) and LA (M = 0.60, SD = 0.40). Significant differences are also found in β band for T8 ($p < 0.05$) between HA (M = 0.47, SD = 0.27) and LA (M = 0.82, SD = 0.57), also exist for P8 ($p < 0.05$) between HA (M = 0.51, SD = 0.44) and LA (M = 0.76, SD = 0.47).

Table 4. The channel list with significantly difference for high-arousal/valence compared with low-arousal/valence (* = $p < 0.05$, ** = $p < 0.01$).

Band	Channel	HA	LA	HV	LV
θ	FP2**	-0.17	0.34		
	F4**	-0.43	0.51		
	AF4**	-0.55	0.65		
	Pz*			0.60	0.38
α	Cz**	0.07	0.87		
	FC1*	0.59	0.75		
	FC2*	0.55	0.71		
	Oz*	0.54	0.64		
	O2**	0.25	0.60		
	O1*	0.81	0.67		
	FP1**			1.01	0.51
	FP2*			0.65	0.58
β	T8*	0.47	0.82	0.50	0.69
	P8*	0.51	0.76		
	T7**			1.12	0.81
	FC5**			0.82	0.58
	CP5*			0.79	0.58
	FC6*			0.45	0.30
	CP6*			0.40	0.49
γ	FC5**			0.78	0.21
	T8**			1.03	0.47
	CP6**			0.58	0.24
	FC6**			0.81	0.33
	T7**			0.94	0.28
	P7**			1.21	0.43
	CP5**			0.65	0.27

As shown in Fig.11, for each channel, we calculate the EEG power of θ, α, β, and γ for all subjects under high-valence and low-valence emotions. The Shapiro-Wilk test indicates the data are normally distributed. The results of pair t-tests show that for the θ band, the parietal lobe activates more for high-valence emotions than the low-valence one. For the α band, the left frontal lobe has higher power for high-valence emotions than the low-valence one. For the β band, we find the lateral temporal lobe has higher power for high-valence emotions than low-valence emotions. Similarly, for the γ band, the lateral temporal lobe activates more for high-valence emotions than low-valence emotions. For the p-value results for the specific channels, as seen from Tab. 4, for the θ band, the paired-samples t-test results show that significant differences are found for Pz ($p < 0.05$) between HV (M = 0.60, SD = 0.28) and LV (M = 0.38, SD = 0.32). For the α band, FP1 ($p < 0.01$) is found to have a significant difference between HV (M = 1.01, SD = 0.68) and LV (M = 0.58, SD = 0.69). Meanwhile, FP2 ($p < 0.05$) is found to have a significant differences between HV (M = 0.65, SD = 0.38) and LV (M = 0.51, SD = 0.47). For the β band, significant differences are found for T8 ($p < 0.05$) between HV (M = 0.50, SD = 0.33) and LV (M = 0.69, SD = 0.48), T7 ($p < 0.01$) between HV (M = 1.12, SD = 0.88) and LV (M = 0.81, SD = 0.76), FC5 ($p < 0.01$) between HV (M = 0.82, SD = 0.66) and LV (M = 0.58, SD = 0.71), CP5 ($p < 0.01$) between HV (M = 0.79, SD = 0.56) and LV (M = 0.58, SD = 0.60), FC6 ($p < 0.01$) between HV (M = 0.45, SD = 0.28) and LV (M = 0.30, SD = 0.47), also exist for CP6 ($p < 0.01$) between HV (M = 0.40, SD = 0.55) and LV (M = 0.49, SD = 0.36). For the γ band, significant differences are found for T7 ($p < 0.01$) between HV (M = 0.94, SD = 0.87) and LV (M = 0.28, SD = 0.33), FC5 ($p < 0.01$) between HV (M = 0.78, SD = 0.63) and LV (M = 0.21, SD = 0.29), CP5 ($p < 0.01$) between HV (M = 0.65, SD = 0.88) and LV (M = 0.27, SD = 0.45), T8 ($p < 0.01$) between HV (M = 1.03, SD = 0.53) and LV (M = 0.47, SD = 0.29), FC6 ($p < 0.01$) between HV (M = 0.81, SD = 0.50) and LV (M = 0.33, SD = 0.44), CP6 ($p < 0.01$) between HV (M = 0.58, SD = 0.63) and LV (M = 0.24, SD = 0.37), also exist for P7 ($p < 0.01$) between HV (M = 1.21, SD = 0.95) and LV (M = 0.43, SD = 0.74).

4.5 Analyse of Hemisphere Asymmetry

As shown in Fig. 10, for 14 pairs of hemisphere asymmetric electrodes, we calculate the significant differences in power of the left and right electrodes for θ , α , β and γ bands under different emotional states. In this section, only the hemisphere asymmetric effects that are significantly below $p < 0.05$ are reported.

For HV and LV, the two-way repeated-measures ANOVA results show that there is a significant emotion $\times$ hemisphere interaction effect at FP1 (left) / FP2 (right) electrodes ($F(1, 27) = 7.654$, $p = 0.041$, η_p^2

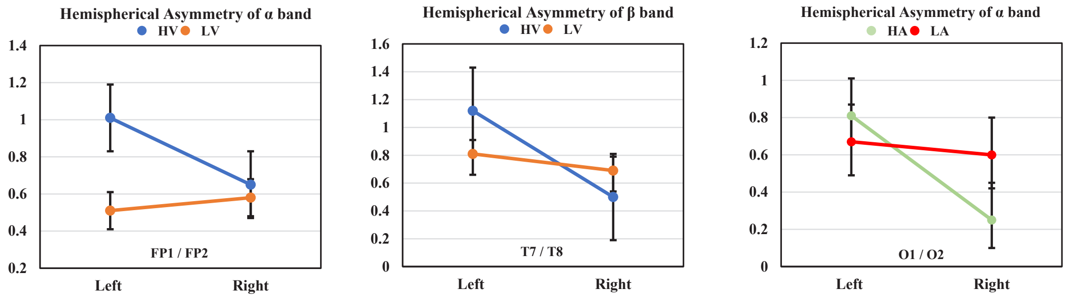


Fig. 10. Hemisphere Asymmetry Effect under High-Arousal / Low-Arousal and High-Valence / Low-Valence.

= 0.663) on the α band. To investigate the interaction of emotion $\times$ hemisphere, we also conduct the ANOVA with a within-factor of hemisphere for each emotion. For HV video stimuli, the left hemisphere evokes significantly higher activity than the right hemisphere ($p < 0.01$). No hemisphere effect is found for the LV video stimuli. Meanwhile, the main effects of emotion ($F(1, 27) = 11.453$, $p = 0.034$, $\eta_p^2 = 0.089$) and hemisphere ($F(1, 27) = 6.865$, $p = 0.033$, $\eta_p^2 = 0.774$) at the FP1 and FP2 electrodes are also found. For the β band, we find a significant emotion $\times$ hemisphere interaction effect at T7 (left) / T8 (right) electrodes ($F(1, 27) = 8.738$, $p = 0.013$, $\eta_p^2 = 0.578$). Similarly, we also conduct the ANOVA with a within-factor of hemisphere for each emotion to investigate the interaction of emotion $\times$ hemisphere. For HV video stimuli, the left hemisphere has significantly higher activity than the right hemisphere ($p < 0.05$). No hemisphere effect is found for the LV video stimuli. The corresponding main effects of emotion ($F(1, 27) = 4.576$, $p = 0.038$, $\eta_p^2 = 0.398$) and hemisphere ($F(1, 27) = 16.875$, $p = 0.026$, $\eta_p^2 = 0.459$) at the T7 and T8 electrodes are also found.

For HA and LA, the two-way repeated-measures ANOVA results show that there is a significant emotion $\times$ hemisphere interaction effect at O1 (left) / O2 (right) electrodes ($F(1, 27) = 26.764$, $p = 0.009$, $\eta_p^2 = 0.876$) on the α band. To investigate the interaction of emotion $\times$ hemisphere, we also conduct the ANOVA with a within-factor of hemisphere for each emotion. For HA video stimuli, the left hemisphere evokes significantly higher activity than the right hemisphere ($p < 0.01$). No hemisphere effect is found for the LA video stimuli. Meanwhile, the main effects of emotion ($F(1, 27) = 6.734$, $p = 0.011$, $\eta_p^2 = 0.605$) and hemisphere ($F(1, 27) = 15.467$, $p = 0.007$, $\eta_p^2 = 0.502$) at the O1 and O2 electrodes are also found.

5 Discussion

Our work aims to assess the potential of the VR emotion induction paradigm, which is the primary basis for affective computing research. Unlike previous studies that only used subjective scales, we have studied the relationship between subjects' subjective and objective neurophysiological responses to find patterns of brain activity for specific emotions. This section will summarize our findings and compare them with previous studies, demonstrating the benefits and potential of VR as a basic computing research tool.

5.1 Subjective Questionnaire

We select VR videos to elicit emotions in the four quadrants of Russell's arousal-valence model, and the projection of VR stimuli on the AV plane is a C-shape (as shown in Fig.5). It is consistent with the previous classic researches of the IAPS, IADS, DEAP and Ascertain [18,19,22]. Besides, the SAM scores of the participants in this study are consistent with the Stanford immersive VR video public database. The low correlation between valence and arousal also indicates that subjects can distinguish these two important concepts well (as shown in Tab. 2). The significant differences between the conditions in terms of the ratings of valence and arousal in Fig. 7 prove the successful emotion elicitation using VR elicitation material. In particular, VR has better performances for high-arousal emotions, indicating the subjects experienced high-intensity emotions in the VR ecological valid scenarios. The emotions induced by low arousal and low valence stimuli are relatively unsuccessful, which may have two reasons: (1) Subjects are more excited when experiencing VR for the first time, making it difficult to induce low arousal. (2) Subjects have a strong presence sense in VR scenarios, since there is a strong correlation between presence and arousal, which leads to a generally high level of arousal for subjects.

Besides, presence is an important evaluation indicator in the VR experience as a mental state. It is generally regarded as a necessary intermediary that allows the virtual environment to activate real emotions [54,55]. Many researchers believe that physiological arousal is one of the main mechanisms that produce a sense of presence [56,57]. Therefore, we have compared the changes in the sense of presence under high and low arousal conditions, and our results back up this theory. A significant difference has been found in SP, INV, and REAL under these two conditions. By analyzing the correlation between INV, REAL, and SP with arousal, we find a strong linear correlation among them (r=0.619 for INV, r=0.643 for REAL, and r=0.826 for SP).

Similarly, the global arousal scores of VR videos and the correlation between arousal and presence are positively correlated (r=0.690, p=0.028 for INV, r=0.667, p=0.031 for REAL, and r=0.810, p=0.003 for SP). In other words, the higher the arousal, the stronger correlation between arousal and presence, vice versa. This finding is consistent with the conclusion of Freeman, which pointed out that only for high arousal conditions there has an obvious positive correlation between arousal and presence [58]. Therefore, we can conclude that the mechanism of VR-induced emotion is linked to the subjects' perception of their presence during the VR experience.

5.2 EEG Pattern

We measure the variation of EEG power under different emotions evoked by VR videos. The results show significant differences in EEG power over different brain regions under the four quadrants of the circumplex model. Based on the analysis of different EEG channels, we find α band of the prefrontal region channels (FP1 and FP2), β band of the lateral temporal region channels (T8, T7, FC5, CP5, CP6, and FC6), γ band of the lateral temporal region channels (T8, T7, FC5, CP5, CP6 FC6, and P7) have a higher power of high-valence emotions than low-valence emotions. Previous neurological studies have shown that β activity reflects emotional and cognitive processes, which often appear when a person is thinking [59]. γ waves frequently appear when people are nervous and excited [60]. Therefore, the power of β and γ is generally increased when dealing with high-valence emotions. This is consistent with previous studies [39,61]. Both the traditional and our VR emotion induction paradigms demonstrate that α, β and γ waves are associated with emotional valence. Still, very few studies on emotional arousal are due to the weak emotion evoked by the traditional emotion induction paradigm. It's thereby difficult to reliably link arousal to stable EEG patterns in specific brain regions. Based on our analysis of different EEG channels, we find channels in the parietal regions (Cz, FC1, and FC2) and channels in the occipital region (Oz and O2) have higher α power for low-arousal emotions than for high-arousal emotions. Previous neurological studies have shown

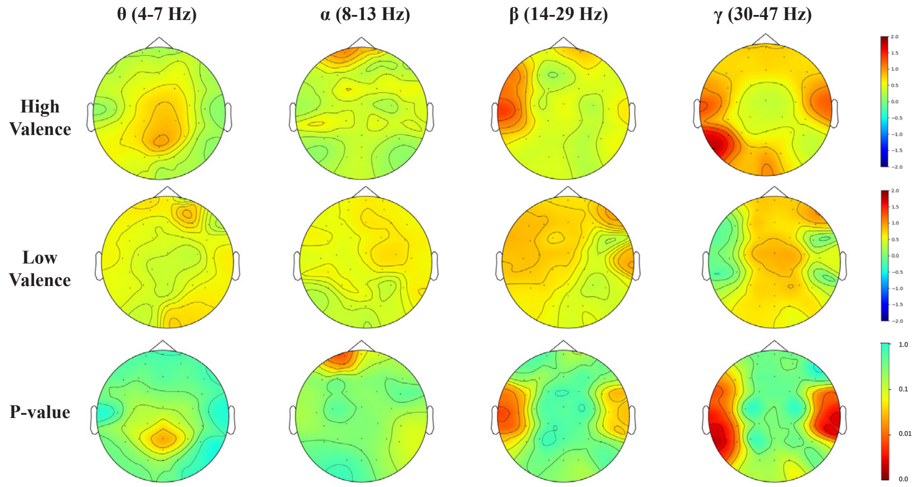


Fig. 11. The EEG power of θ (4-7Hz), α (8-13Hz), β (14-29Hz), and γ (30-47Hz) over all subjects for high-valence and low-valence.

that α activity reflects attentional processing, which often appears when a person is relaxed and calm [59]. Our finding can be interpreted as when participants are experiencing low-arousal emotions, they are more relaxed and have a higher α power in the parietal and occipital regions.

We also analyze the hemisphere asymmetry effect induced by VR videos. The results show that the brain has the properties of lateralized activation when processing emotion in a VR environment. We find only for high-valence emotions, significant differences in the power of the β band in the temporal lobe of the left (T7) and right (T8) hemispheres channel. This is consistent with previous studies [59]. However, no lateralization has been found for low-valence emotions. There is also no lateralization in the γ band. Meanwhile, we find that there is a lateralized activation of emotion in the frontal lobe. For high-valence emotions, a higher α power of the left hemisphere channel (FP1) is found compared with the right hemisphere channel (FP2), while the opposite is observed for low-valence emotion. This finding also matches previous research, proving a higher activation degree in the left hemisphere under high valence emotions [62]. Although several studies have shown the relationship between valence and hemispheric asymmetry. However, for emotional arousal, the lateralization of brain activation is still unclear and lacks relevant literature, especially in VR scenarios. Therefore, our research fills this gap, and an interesting finding is that the α band in the occipital lobe is also lateralized under high-arousal emotions. Higher α power is found over the left channel (O1) compared with the right channel (O2), but it is not found for low-arousal emotions. We speculate that the reason for this phenomenon is that during the VR experiment, the subjects concentrate on the visual stimuli of the immersive scene, which leads the brain to generate more attention and memory information. α waves are closely related to attention and memory formation. As a result, the occipital lobe of the brain has the characteristics of lateralization. In summary, the mechanisms of emotional brain function and human emotion modeling are still unclear. There are few studies combining VR and EEG to study emotion. We hope to better understand the physiological mechanisms behind human emotions using VR ecologically effective scenarios.

6 Limitation

Our current research still has some limitations given the exploratory nature of this work. First of all, our dataset has a limited age distribution that exclusively collects EEG signals from college students, since young pupils are more adept at experiments and more enthusiastic about VR. We have currently done experiments with 28 subjects, with detailed questionnaires, original data, and preprocessed data available. In the future, our dataset will be strengthened by adding subjects' EEG data from a wider age group and shared for public research. Second, subjects are not allowed to turn their heads excessively during the experiment, which may affect their experiences. In the future, we will conduct specific experiments to analyze how head movements affect the quality of EEG signals and the accuracy of emotion recognition. Various movement intensities (a combination of different movement amplitudes and speeds) will be helpful to explore the best head movement intensity parameters in VR experiments. Third, previous studies have demonstrated that VR can induce higher levels of emotional arousal than traditional media by subjective scales [10]. Thus, due to the long time experiment could cause excessive fatigue to the subject, reducing the experimental effect, we only explored the validity of the VR emotion induction paradigm without comparison with the traditional 2D displays. Finally, since most artifacts such as EOG, ECG, and EMG are dominant below 4 Hz and power line noise usually lies at 50 Hz, while information at 4–47 Hz has the strongest emotional association and dominates the field of affective computing [6]. To ensure the rigor and correctness of this exploratory research and obtain a purer signal, we carefully filtered out the δ and high γ bands. In future research, we will further extract the features of δ bands for emotion recognition to verify their validity.

7 Conclusion

In this paper, we provide new insights into the selection of emotion evoked paradigms. We conclude that VR has a powerful ability to make subject's high sense of presence and evoke real emotions in a more natural and realistic way, especially for high-arousal. We also establish association maps of emotional states and related brain regions and EEG features. In high-arousal emotions, the power of α waves is found to be lower in the parieto-occipital regions than in low-arousal emotions. High-valence emotions have more β and γ waves activity in the temporal lobe than low-valence emotions. The hemispheric asymmetry analysis result shows that α waves in prefrontal regions and β waves in temporal regions have lateralized activation only for high-valence emotions. In particular, since VR has the unique ability to induce high-arousal emotions, we find α waves in occipital regions have the properties of lateralized activation only for high-arousal emotions, which extends the previous conclusions on the neurophysiology of emotional arousal. These neural patterns related to different emotions are consistent and stable across individuals and could be used as effective indicators to reliably label and evaluate the true evoked emotion. It explains why the VR induction paradigm is important in finding biomarkers of specific emotional states, which could fundamentally promote the computational models for affective computing. Our study combines EEG and a naturalistic immersive VR experience and paves the way to study human emotions in more realistic and naturalistic settings. Along with our pioneering heading, we hope to create publicly accessible databases of VR stimulus material in the future so that we can make consistent comparisons across studies and start a new direction with an active data collection mechanism using VR.

ACKNOWLEDGMENTS

This work was supported by National Natural Science Foundation of China (No.61872020, 62172437, U20A20195, 62102208, 62002010), Beijing Natural Science Foundation under Grant (4214066), Beijing Advanced Innovation Center for Biomedical Engineering under Grant ZF138G1714, National Science Foundation of USA under Grants IIS-1715985 and IIS-1812606, and Global Visiting Fellowship of Bournemouth University.

This work was supported by the Research Program Funds of the Collaborative Innovation Center of Assessment toward Basic Education Quality at Beijing Normal University: 2021-01-131-BZK01 supported by the Fundamental Research Funds for the Central Universities:310422116.

REFERENCES

[1] J. R. Fontaine, K. R. Scherer, and C. Soriano, *Components of emotional meaning: A sourcebook*. Oxford University Press, 2013.

[2] G. Mohammadi and P. Vuilleumier, "A multi-componential approach to emotion recognition and the effect of personality," *IEEE Transactions on Affective Computing*, vol. PP, no. 99, pp. 1–1, 2020.

[3] A. Moors, P. C. Ellsworth, K. R. Scherer, and N. H. Frijda, "Appraisal theories of emotion: State of the art and future development," *Emotion Review*, vol. 5, no. 2, pp. 119–124, 2013.

[4] K. R. Scherer, A. Schorr, and T. Johnstone, *Appraisal processes in emotion: Theory, methods, research*. Oxford University Press, 2001.

[5] N. H. Frijda, *The laws of emotion*. Psychology Press, 2017.

[6] S. Katsigiannis and N. Ramzan, "Dreamer: A database for emotion recognition through eeg and ecg signals from wireless low-cost off-the-shelf devices," *IEEE journal of biomedical and health informatics*, vol. 22, no. 1, pp. 98–107, 2017.

[7] S. M. Hofmann, F. Klotzsche, A. Mariola, V. V. Nikulin, A. Villringer, and M. Gaebler, "Decoding subjective emotional arousal during a naturalistic vr experience from eeg using lstms," in *IEEE International Conference on Artificial Intelligence and Virtual Reality (AIVR)*, 2018, pp. 128–131.

[8] R. Somarathna, T. Bednarz, and G. Mohammadi, "Virtual reality for emotion elicitation–a review," *arXiv preprint arXiv:2111.04461*, 2021.

[9] E. Bastug, M. Bennis, M. Médard, and M. Debbah, "Toward interconnected virtual reality: Opportunities, challenges, and enablers," *IEEE Communications Magazine*, vol. 55, no. 6, pp. 110–117, 2017.

[10] F. Pallavicini, A. Pepe, and M. E. Minissi, "Gaming in virtual reality: What changes in terms of usability, emotional response and sense of presence compared to non-immersive video games?" *Simulation & Gaming*, vol. 50, no. 2, pp. 136–159, 2019.

[11] A. Kim, M. Chang, Y. Choi, S. Jeon, and K. Lee, "The effect of immersion on emotional responses to film viewing in a virtual environment," in *IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, 2018, pp. 601–602.

[12] M. Moghimi, R. Stone, and P. Rotshtein, "Affective recognition in dynamic and interactive virtual environments," *IEEE Transactions on Affective Computing*, vol. 11, no. 1, pp. 45–62, 2017.

[13] S. M. Alarcao and M. J. Fonseca, "Emotions recognition using eeg signals: A survey," *IEEE Transactions on Affective Computing*, vol. 10, no. 3, pp. 374–393, 2017.

[14] W. L. Zheng and B. L. Lu, "Investigating critical frequency bands and channels for eeg-based emotion recognition with deep neural networks," *IEEE Transactions on Autonomous Mental Development*, vol. 7, no. 3, pp. 162–175, 2015.

[15] Y. J. Liu, M. Yu, G. Zhao, J. Song, Y. Ge, and Y. Shi, "Real-time movie-induced discrete emotion recognition from eeg signals," *IEEE Transactions on Affective Computing*, vol. 9, no. 4, pp. 550–562, 2017.

[16] Y. Zhang, G. Zhao, Y. Shu, Y. Ge, and X. Sun, "Cped: A chinese positive emotion database for emotion elicitation and analysis," *IEEE Transactions on Affective Computing*, vol. PP, no. 99, pp. 1–1, 2021.

[17] M. M. Bradley and P. J. Lang, "Affective norms for english text (anet): Affective ratings of text and instruction manual," *Techical Report. D-1, University of Florida, Gainesville, FL*, 2007.

[18] P. J. Lang, M. M. Bradley, B. N. Cuthbert *et al.*, "International affective picture system (iaps): Technical manual and affective ratings," *NIMH Center for the Study of Emotion and Attention*, vol. 1, no. 39-58, p. 3, 1997.

[19] S. Koelstra, C. Muhl, M. Soleymani, J. S. Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, and I. Patras, "Deap: A database for emotion analysis; using physiological signals," *IEEE transactions on affective computing*, vol. 3, no. 1, pp. 18–31, 2011.

[20] M. Soleymani, J. Lichtenauer, T. Pun, and M. Pantic, "A multimodal database for affect recognition and implicit tagging," *IEEE transactions on affective computing*, vol. 3, no. 1, pp. 42–55, 2011.

[21] J. A. M. Correa, M. K. Abadi, N. Sebe, and I. Patras, "Amigos: A dataset for affect, personality and mood research on individuals and groups," *IEEE Transactions on Affective Computing*, vol. 12, no. 2, pp. 479–493, 2018.

[22] R. Subramanian, J. Wache, M. K. Abadi, R. L. Vieriu, S. Winkler, and N. Sebe, "Ascertain: Emotion and personality recognition using commercial sensors," *IEEE Transactions on Affective Computing*, vol. 9, no. 2, pp. 147–160, 2016.

[23] G. Rizzolatti and L. Craighero, "The mirror-neuron system," *Annu. Rev. Neurosci.*, vol. 27, pp. 169–192, 2004.

[24] G. Chanel, C. Rebetez, M. Bétrancourt, and T. Pun, "Emotion assessment from physiological signals for adaptation of game difficulty," *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, vol. 41, no. 6, pp. 1052–1063, 2011.

[25] M. B. Powers and P. M. Emmelkamp, "Virtual reality exposure therapy for anxiety disorders: A meta-analysis," *Journal of anxiety disorders*, vol. 22, no. 3, pp. 561–569, 2008.

[26] L. Petrescu, C. Petrescu, O. Mitruț, G. Moise, A. Moldoveanu, F. Moldoveanu, and M. Leordeanu, "Integrating biosignals measurement in virtual reality environments for anxiety detection," *Sensors*, vol. 20, no. 24, p. 7088, 2020.

[27] M. Volante, S. V. Babu, H. Chaturvedi, N. Newsome, E. Ebrahimi, T. Roy, S. B. Daily, and T. Fasolino, "Effects of virtual human appearance fidelity on emotion contagion in affective inter-personal simulations," *IEEE transactions on visualization and computer graphics*, vol. 22, no. 4, pp. 1326–1335, 2016.

[28] R. Cao, L. Zou Williams, A. Cunningham, J. Walsh, and B. H. Thornas, "Comparing the neuro-physiological effects of cinematic virtual reality with 2d monitors," in *IEEE Virtual Reality and 3D User Interfaces (VR)*, 2021.

[29] J. N. Voigt Antons, R. Spang, T. Kojic, L. Meier, and S. Muller, "Don't worry be happy - using virtual environments to induce emotional states measured by subjective scales and heart rate parameters," in *IEEE Virtual Reality and 3D User Interfaces (VR)*, 2021.

[30] J. Marín-Morales, J. L. Higuera Trujillo, A. Greco, J. Guixeres, C. Llinares, E. P. Scilingo, M. Alcañiz, and G. Valenza, "Affective computing in virtual reality: emotion recognition from brain and heartbeat dynamics using wearable sensors," *Scientific reports*, vol. 8, no. 1, pp. 1–15, 2018.

[31] Y. P. Lin, C. H. Wang, T. P. Jung, T. L. Wu, S. K. Jeng, J. R. Duann, and J. H. Chen, "Eeg-based emotion recognition in music listening," *IEEE Transactions on Biomedical Engineering*, vol. 57, no. 7, pp. 1798–1806, 2010.

[32] A. R. Damasio, T. J. Grabowski, A. Bechara, H. Damasio, L. L. Ponto, J. Parvizi, and R. D. Hichwa, "Subcortical and cortical brain activity during the feeling of self-generated emotions," *Nature neuroscience*, vol. 3, no. 10, pp. 1049–1056, 2000.

[33] M. Soleymani, S. Asghari-Esfeden, Y. Fu, and M. Pantic, "Analysis of eeg signals and facial expressions for continuous emotion detection," *IEEE Transactions on Affective Computing*, vol. 7, no. 1, pp. 17–28, 2015.

[34] C. D. B. Luft and J. Bhattacharya, "Aroused with heart: Modulation of heartbeat evoked potential by arousal induction and its oscillatory correlates," *Scientific reports*, vol. 5, no. 1, pp. 1–11, 2015.

[35] J. A. Coan and J. J. Allen, "Frontal eeg asymmetry as a moderator and mediator of emotion," *Biological psychology*, vol. 67, no. 1-2, pp. 7–50, 2004.

[36] L. A. Schmidt and L. J. Trainor, "Frontal brain electrical activity (eeg) distinguishes valence and intensity of musical emotions," *Cognition & Emotion*, vol. 15, no. 4, pp. 487–500, 2001.

[37] G. Zhao, Y. Zhang, and Y. Ge, "Frontal eeg asymmetry and middle line power difference in discrete emotions," *Frontiers in behavioral neuroscience*, p. 225, 2018.

[38] F. Galvão, S. M. Alarcão, and M. J. Fonseca, "Predicting exact valence and arousal values from eeg," *Sensors*, vol. 21, no. 10, p. 3414, 2021.

[39] W. L. Zheng, J. Y. Zhu, and B. L. Lu, "Identifying stable patterns over time for emotion recognition from eeg," *IEEE Transactions on Affective Computing*, vol. 10, no. 3, pp. 417–429, 2017.

[40] J. I. Vallade, R. Kaufmann, B. N. Frisby, and J. C. Martin, "Technology acceptance model: Investigating students' intentions toward adoption of immersive 360 videos for public speaking rehearsals," *Communication*

Education, vol. 70, no. 2, pp. 127–145, 2021.
[41] B. J. Li, J. N. Bailenson, A. Pines, W. J. Greenleaf, and L. M. Williams, “A public database of immersive vr videos with corresponding ratings of arousal, valence, and correlations between head movements and self report measures,” *Frontiers in psychology*, vol. 8, p. 2116, 2017.
[42] J. A. Russell, “A circumplex model of affect.” *Journal of personality and social psychology*, vol. 39, no. 6, p. 1161, 1980.
[43] D. Jeong, S. Yoo, and J. Yun, “Cybersickness analysis with eeg using deep learning algorithms,” in *IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, 2019, pp. 827–835.
[44] B. Meuleman and D. Rudrauf, “Induction and profiling of strong multi-componential emotions in virtual reality,” *IEEE Transactions on Affective Computing*, vol. 12, no. 1, pp. 189–202, 2018.
[45] M. M. Bradley and P. J. Lang, “Measuring emotion: the self-assessment manikin and the semantic differential,” *Journal of behavior therapy and experimental psychiatry*, vol. 25, no. 1, pp. 49–59, 1994.
[46] T. Schubert, F. Friedmann, and H. Regenbrecht, “The experience of presence: Factor analytic insights,” *Presence: Teleoperators & Virtual Environments*, vol. 10, no. 3, pp. 266–281, 2001.
[47] T. Radüntz, J. Scouten, O. Hochmuth, and B. Meffert, “Eeg artifact elimination by extraction of ica-component features using image processing algorithms,” *Journal of neuroscience methods*, vol. 243, pp. 84–93, 2015.
[48] A. Delorme and S. Makeig, “Eeglab: an open source toolbox for analysis of single-trial eeg dynamics including independent component analysis,” *Journal of neuroscience methods*, vol. 134, no. 1, pp. 9–21, 2004.
[49] M. Chaumon, D. Bishop, and N. A. Busch, “A practical guide to the selection of independent components of the electroencephalogram for artifact correction,” *J Neurosci Methods*, vol. 250, pp. 47–63, 2015.
[50] X. W. Wang, D. Nie, and B. L. Lu, “Eeg-based emotion recognition using frequency domain features and support vector machines,” in *International conference on neural information processing*, 2011, pp. 734–743.
[51] Y. Roy, H. Banville, I. Albuquerque, A. Gramfort, T. H. Falk, and J. Faubert, “Deep learning-based electroencephalography analysis: a systematic review,” *Journal of neural engineering*, vol. 16, no. 5, p. 051001, 2019.
[52] O. M. Solomon, “Psd computations using welch’s method,” *NASA STI/Recon Technical Report N*, vol. 92, 1991.
[53] F. J. Harris, “On the use of windows for harmonic analysis with the discrete fourier transform,” *IEEE Proceedings*, vol. 66, no. 1, pp. 51–83, 1978.
[54] G. Riva, F. Mantovani, C. S. Capideville, A. Preziosa, F. Morganti, D. Villani, A. Gaggioli, C. Botella, and M. Alcañiz, “Affective interactions using virtual reality: the link between presence and emotions,” *Cyberpsychology & behavior*, vol. 10, no. 1, pp. 45–56, 2007.
[55] T. Baumgartner, D. Speck, D. Wettstein, O. Masnari, G. Beeli, and L. Jäncke, “Feeling present in arousing virtual reality worlds: prefrontal brain regions differentially orchestrate presence experience in adults and children,” *Frontiers in human neuroscience*, vol. 2, p. 8, 2008.
[56] M. Meehan, B. Insko, M. Whitton, and F. P. Brooks Jr, “Physiological measures of presence in stressful virtual environments,” *Acm transactions on graphics (tog)*, vol. 21, no. 3, pp. 645–652, 2002.
[57] T. Baumgartner, L. Valko, M. Esslen, and L. Jäncke, “Neural correlate of spatial presence in an arousing and noninteractive virtual reality: an eeg and psychophysiology study,” *CyberPsychology & Behavior*, vol. 9, no. 1, pp. 30–45, 2006.
[58] J. Freeman, J. Lessiter, K. Pugh, E. Keogh *et al.*, “When presence and emotion are related, and when they are not,” *8th annual international workshop on presence*, pp. 21–23, 2005.
[59] W. J. Ray and H. W. Cole, “Eeg alpha activity reflects attentional demands, and beta activity reflects emotional and cognitive processes,” *Science*, vol. 228, no. 4700, pp. 750–752, 1985.
[60] R. Jenke, A. Peer, and M. Buss, “Feature extraction and selection for emotion recognition from eeg,” *IEEE Transactions on Affective computing*, vol. 5, no. 3, pp. 327–339, 2014.
[61] S. K. Hadjidimitriou and L. J. Hadjileontiadis, “Toward an eeg-based recognition of music liking using time-frequency analysis,” *IEEE Transactions on Biomedical Engineering*, vol. 59, no. 12, pp. 3498–3510, 2012.
[62] G. L. Ahern and G. E. Schwartz, “Differential lateralization for positive and negative emotion in the human brain: Eeg spectral analysis,” *Neuropsychologia*, vol. 23, no. 6, pp. 745–755, 1985.