Enhancing Audience Engagement in Performing Arts Through an Adaptive Virtual Environment with a Brain-Computer Interface

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ABSTRACT
Audience engagement is an important indicator of the quality of the performing arts but hard to measure. Psychophysiological measurements are promising research methods for perceiving and understanding audience's responses in real-time. Currently, such research are conducted by collecting biometric data from audience when they are watching a performance. In this paper, we draw on techniques from brain-computer interfaces (BCI) and knowledge from quality of performing arts to develop a system that monitor audience engagement in real time using electroencephalography (EEG) measurement and seek to improve it by triggering the adaptive performing cues when the engagement level decreased. We simulated the immersive theatre performances to provide audience a high-fidelity visual-audio experience. An experimental evaluation is conducted with 48 participants during two different performance studies. The results showed that our system could successfully detect the decreases in audience engagement and the performing cues had positive effects on regain audience engagement. Our research offers the guidelines for designing theatre performances from the audience's perception.

Author Keywords
Audience engagement; brain-computer interface (BCI); electroencephalography (EEG); adaptive user interface

ACM Classification Keywords
H.5.2. Information interfaces and presentation: User Interfaces: Input devices and strategies, Evaluation/methodology, User-centered design; J.5. Computer Applications: Arts and Humanities: Performing arts

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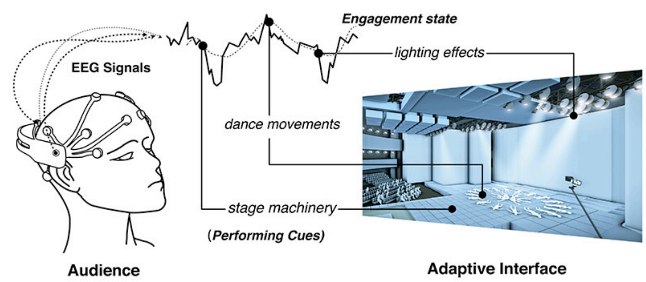

Figure 1. The audiences interact with an adaptive virtual environment of theatre performance that monitors their reactions through the measured EEG signals and adaptively creates real-time performing cues to improve audience engagement.

INTRODUCTION
Audience engagement refers to the effect that a show arouses audience emotions, stimulates their physical reaction, and triggers their cognitive development [28]. It is generally difficult for the audiences to stay focused on the theatre performing arts (such as opera, dance, etc.) with less audience participation, compared with the stand-up comedies and the live music shows [29]. The importance of audience feedback has been detailed in an extensive literature review and the gauging of audience engagement has proved to be a key measure of quality in the performing arts [27]. However, during the design stage of theatre performance arts, it is a challenge for stage directors to predict the audience engagement.

To address this issue, we need to answer the following questions: First, how to measure audience engagement in theatre performing arts? Second, how could we design and generate adaptive performing cues as immediate stimulus to engage the audience and response to their emotional feedback without disrupting the performance? Finally, how to integrate both the measurement system and the adaptive performing cues in one system, which enables the stage directors to improve the design of theatre performances.

Recent development in the BCI techniques has enabled us to measure the audience engagement with off-the-shelf devices with reasonable accuracy. In addition, more and more stage designers have adopted digital performance technique to improve their design. The digital performance technique provides the stage designer a virtual environment in which they can create, manipulate, and test the performance elements in a totally interactive way.

Based on this two development, we seek to improve audience engagement by proposing an interactive design tool that measures the audience engagement and adaptively creates immersive theatre performance experience in a virtual environment in real-time. To do that, we propose a novel approach that combines neuroscience and theatre performing arts. We measure the audience engagement in real-time using neural signals obtained from an off-the-shelf wireless EEG headset. The immersive theatre performance experience is generated by a game engine and can be adjusted interactively. The concept of the proposed system is illustrated in Figure 1.

RELATED WORK

Digital Performance

Theatre and performance in digital culture has been developed from simulation to embeddedness since the emerging of advanced technologies, including 3D modeling of theatre architecture, animated scenery, performance simulation using motion capture, along with simulations of audience interactions and hypermedia content [19].

Digital performance applies digital technology to reconstruct and archive performing arts events. The technique helps performance director and actor to establish a virtual environment to generate the performance scenes, to rehearse the theatre performance, and adjust the narrative structures [10]. However, current digital performance techniques only concentrate on the design of the performance itself without combining the audience emotional states. It has not acknowledged that the audience response could also contribute to the performance.

Brain-Computer Interface

BCIs are rapidly growing technology that draws on brain signals as user input. A BCI is a system that provides computer application with access to real-time information about user cognitive state, on the basis of measured brain activity [31]. In HCI viewpoint, the BCI systems can be categorized into three types: the active BCI, the reactive BCI, and the passive BCI. The active BCIs allow users directly communicate with a technical system by consciously control mental activity. However, these systems usually require extensive tuning and training on both the system and the user, and are rarely generalizable across multiple users [2, 25]. The reactive BCIs derive outputs from the brain activities arising in response to the external stimulations, and the modulated activity is mapped to an artificial control signal. Thus, the attention of the user focus in visual, auditory, or tactile perception is modulated for the purpose of communication, and thereby occupied.

Current research has shown a paradigm shift towards passive BCI systems, which implicitly monitor user conscious and unconscious brain activity [35]. The brain activity is assimilated to an input and can be used to adapt the application to the user's mental state [12]. The system has already been used for user and machine errors detection and adapt user cognitive load [12, 13, 31]. Adaptive interfaces based on passive BCIs, generating a loop that iterates between measurement, evaluation and redesign to create interfaces that automatically adapt depending on the cognitive state of the user [31]. In order to provide pleasant and optimal user experience, user current cognition state and the context-sensitivity become the key information of the interactive system.

Sensing Audience in Performing Arts

Current audience engagement measurement divides into two categories: the explicit and the implicit. Explicit measurement includes post-performance surveys, focus groups, audience interviews and real-time response devices. Physiological measures could be used to measure implicit engagement biometrically [18]. The implicit measurement technique includes the Galvanic Skin Response (GSR), electroencephalograph (EEG), electromyography (EMG), and functional magnetic resonance imaging (fMRI), etc.

The seminal work of Celine Latulipe provides an extensive overview of research in audience engagement [18]. Based on the empirical and theoretical work of Peter Lang [19], she explored how GSR can be used to provide real-time audience feedback to performers while watching different performance videos. The GSR measures the conductivity of user's skin, which response to autonomic nervous system arousal [5]. The similar measurement could also be found in recent work from Chen Wang [34], which extended the experimental paradigm by simultaneously measuring a group of participants in a live performance. However, even though these studies have proved that GSR measurement is a valid representation of audience engagement, neither of their systems has content-related performing cues that automatically adapt depending on the cognitive state of the audience.

There are few studies using physiological measurements for creating adaptive scenes in performing arts. For example, Many Worlds, a research of developing adaptive interface that watches audience members as they watch it, allowing them to influence the sequence of scenes as the film unfolds [14]. The researchers required four volunteers from the audience to be attached to sensors, which monitor and track their heart rate, EEG brain waves, perspiration, and muscle tension respectively. An off-the-peg software tools utilized real-time analysis to change the direction or the scenes in a movie.

There are also possibilities in measuring facial expressions or using EMG to measure facial muscle activations. These data are more linked to audience's emotions, but have poor form factors for detecting in a theatre setting. Because the facial expressions during a performance may not be particularly illuminating, and it is difficult to recognize massive parallel facial expression of an audience. It's also possible to measure neural signal. Calvo-Merino and her colleagues presented their neuroscientific study of aesthetic perception in the context of the performing arts [7]. They use fMRI to investigate the brain areas whose activity during passive watching of dance stimuli was related to independent aesthetic evaluation of the same stimuli. The study shows that there are visual and sensorimotor brain areas in the occipital cortices and right premotor cortex, which have an automatic aesthetic response to dance. The result provides us insight into how visual stimulus mechanism could improve the evaluation of performing arts. However fMRI, much like fNIRS, is mostly be used to build functional maps of brain activity [31].

Measuring Audience Engagement with EEG

Electroencephalography (EEG) is a well-studied method of non-invasive BCIs to measure the brain's electrical activity [3, 23, 33]. The greatest advantage of EEG is high temporal resolution, complex patterns of neural activity can be recorded occurring within fractions of a second after a stimuli has been applied. But, it provides low spatial resolution compared to fMRI, which makes it difficult to determine where the signals originated from in the brain. Further, eye movements, muscle noise, heart signals, and line noise often produce distracting artifacts in EEG recording. To overcome these issues, we could remove artifacts by filtering the noise signal while preserving the essential EEG signals.

EEG frequencies (see Figure 2) have been extensively studied and can provide insight into user mood and emotions such as excitement, meditation, pleasure and frustration [9, 12, 21]. EEG measures are also sensitive to cognitive states including engagement and attention, working modality and perception of user machine errors [9, 11, 32]. The following formula is widely used to estimate participant task engagement based on the amplitudes of α, β, and θ waves, the EEG measured engagement is a ratio value without a unit [26].

$$EEG \quad engagement = \frac{\beta}{\alpha + \theta}$$

Now, commercially available, low-cost wireless EEG headsets have made this approach even more feasible [24]. The headset can be used in general public setting, offers no risk to the user, and do not require specific knowledge or training before use it. Also, EEG has been used make accurate classifications of various cognitive tasks [20, 31]. FOCUS [15] and LET'S LEARN [1] designed EEG-augmented reading system using content-related videos to improve user's reading engagement. However, the systems are not been formally studied. PAY ATTENTION [30] is relevant to our research, it designs an embodied story-telling agent, using adaptive spoken volume and gestures to attract user's attention when detect their engagement level decrease. Although the system could successfully detect the significant drops and regain user attention, it has not specified that whether various changes of behavioral cues affect audience differently. Our research based on the non-invasive, passive BCI system to monitor audience engagement and enhance the user-system performance by creating an interface that response to user's cognitive state controlled by EEG data.

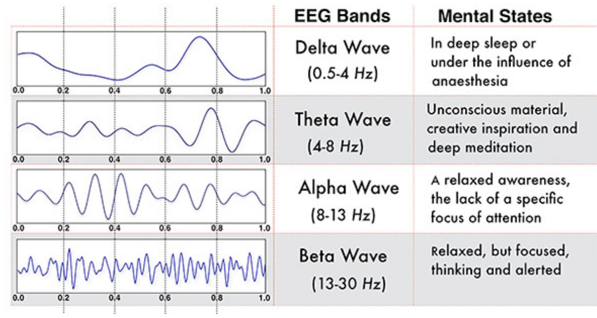

Figure 2. EEG bands and their frequencies, specifications.

In summary, no BCI technique has been used to improve the design quality of the performance art from the audience perspective. In addition, there are few virtual environment performances available that enable the stage designer to adjust the performing cues and evaluate the overall effect in an interactive way. We design an immersive theatre performance virtual environment to create adaptive content-related performing cues to improve audience engagement in various conditions based on the user's unconscious engagement level measured in real-time.

SYSTEM DESIGN

In this section, we present the design and implementation detail of the proposed system.

System Overview

The proposed system includes three levels: the interface level, the logic level, and the engine level. The interface level includes the input interface, which is an Emotiv^{TM} EEG headset, and the output interface, which is a 3D projection system. The logic level consists of parsing the EEG data and determining when to initiate the performing cues. It also includes the software module that simulates and renders the virtual scenes of a show under the design process. The engine level includes the main functions developed based on CryEngine^{TM}, a game engine.

The user of the system wears an Emotiv^{TM} EEG headset, which captures the EEG signal during the experiments. The obtained EEG signal then was analyzed to determine the levels of audience engagement. Our algorithm determines the decreases of audience engagement and triggers the performing cues to regain the values. A virtual environment, including the main performance contents and the performing cues, is implemented via CryEngine^{TM}. The final results of the virtual performance contents is rendered and projected on an immersive 3D circular-screen.

Measuring EEG-based Engagement

In our study, we integrated EEG into the proposed system to determine the right moment to employ performing cues. The Emotiv™ headset consists of 14 electrode sensors and 2 bipolar reference electrodes spatially organized using the International 10-20 System [16]. It connects wirelessly via Bluetooth and a USB dongle to a computer. It does not require any special training and is comfortable and usable enough for audience to use in a simulated theatre environment. Once the system detected the loss of engagement, the content-related performing cues should be evoked and regained audience engagement in a certain time.

The Emotiv™ hardware filter the signal via the common mode rejection, the digital notch filters at 50Hz and 60Hz, as well as the proprietary algorithms to remove EMG artifacts (such as eye movements, eye blinks, muscle activities) and other noise. The device samples at a rate of 128Hz and is sensitive to frequencies in the range of 0.2-45Hz, which broken into Delta, Theta, Alpha, and Beta waves using Fast Fourier Transforms. For the purpose of our research, when estimating audience engagement with Emotiv™, we used two pairs of electrodes (O1- O2, T7-T8), for those are highly relevant to the visual attention and the positive arousals respectively [6, 17]. The EEG levels for Alpha, Beta, and Theta frequencies were read in from the headset. We estimated the engagement values $E(i)$ by averaging obtained data from the four electrodes based on the above EEG engagement formula. We smoothed the engagement values $E(i)$ by using the moving average filter:

$$E_s(n) = \frac{1}{N} \sum_{i=n-N+1}^{n} E(i)$$

Where $E_s(n)$ corresponds to the smoothed engagement value at n frame, $E(i)$ is the engagement value at i frame, and N is a 10-second timeframe, which is chosen after pre-testing to identity minimum times that ensure sufficient data to accurately make predictions.

Detecting Decreases and Re-engagement

EEG signal measured by Emotiv™ is user-dependent, which makes it difficult to determine the state of engagement for various audiences. We set two thresholds as follows, for the individual audience to separate three distinctive status of audience engagement $S(n)$: positive arousals (1); stable engagement (0), and less interests (-1) from an audience engagement curve $E_s(n)$.

Detecting decreasing thresholds

$$S(n) = -1, \textit{when} \quad E_s(n) - E_s(n-1) < 0 \quad \textit{and} \quad E_s < \bar{E}$$

Where $S(n)$ = -1 represents the status of less interests, n is the current frame number, $\bar{E}$ is the average engagement value of all $E(i)$ from the beginning of EEG recording to the current frame. This creates a constantly updating "average" engagement level (gray curve in Figure 3) for each individual audience. When $S(n)$ output -1, a drop point was marked (see Figure 3) and a performing cue should be triggered and displayed at the same time.

The success of re-engaging audience

Similarly, another threshold (or the re-engaging threshold) is set to determine whether the performing cues re-engaged audience successfully and how the performing cues would affect the engagement values differently.

$$S(n) = 1, \textit{when} \quad E_s(n) - E_s(n-1) > 0 \quad \textit{and} \quad E_s > \bar{E}$$

If $S(n)$ output is 1, the performing cue was determined to successfully re-engage the audience. We set up a 15-second interval (based on pre-test results) as response time due to a 5-second delay from the smoothed engagement value.

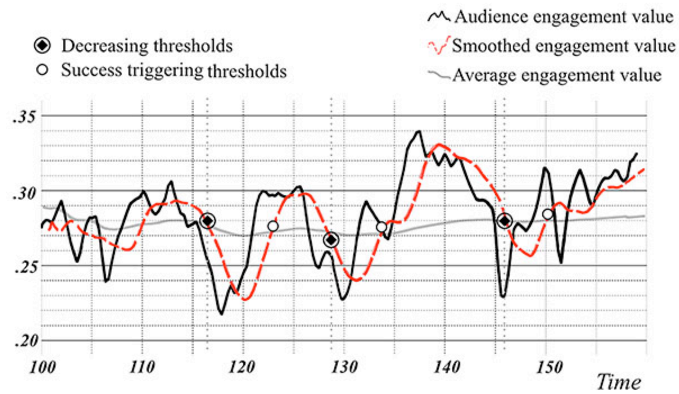

Figure 3. A preliminary test by using our algorithm, when detecting the drops, the adaptive cues will be triggered to regain audience engagement.

Theatre Performing Cues

We design the performing cues based on the classic theatre performing theory. A theatre performance is a synthetic process, which comprises of the performers' acting and the dynamic stage machinery. The stage machinery is designed for the production of theatrical effects, such as the scenic design, the lighting, the sound effects, and the special effects (illusions of the supernatural or magical, see Figure 4) [8].

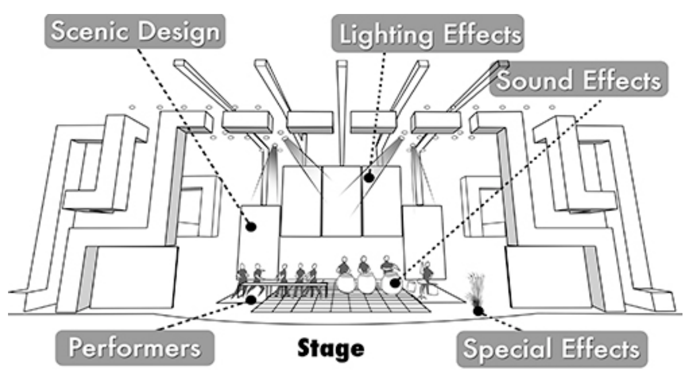

Figure 4. A basic structure of theatre performance.

The basic theatre performing cues is listed in Table 1. The scenic design (partnered with lighting design) helps the audience see and identify the location of the play [22]. In our study, we adjusted the stage set by dynamically moving the display blocks, which can be assembled into various shapes with textures controlled by the video players. The stage special effects, such as smoke or fog, invoke a specific sense of mood or atmosphere that has been reported to enrich performing scenarios and attract the audience immediately. The lighting effects helps the audience focus only on certain areas, performers, props, and or a set piece, which may be the main focus or the emphasis in that scene. The sound effects are the artificial reproduction of sounds that intend to intensify actions and supply realism in the theatre [8].

Theatre Performing Cues		**Objects**	**Dynamic Changes**
Stage Machinery	Scenic Design	Background screen; flying system; stage floor	*Horizontal, vertical movement; multi-angled rotating; dynamic matching*
	Special effects	Particle system; theatre property	*Sunlight, smoke, firework, random glowing trail…*
	Lighting effects	Light installations	*Color, size, intensity, shape, direction changing; focusing, spotlighting, composing…*
	Sound effects	Program music; actor voice; instrument	*Volume, rhythm, emotion, scene effects changing*
Performers	Motion	Main actor; figurant	*Complex movement, creative interaction*
	Costume	Apparel; accessories	*Color, shape, texture changing*

Table 1. The specification of theatre performing cues.

For instance, we could simulate sounds like shouts, horse's hooves or any other effect, which either too vast in scope or too complex to be present on stage. For the performers, research in the field of neuroaesthetics attempts to identify the brain processes underlying aesthetic experience for actors' motion, the work shows that the audience are most engaged by the large, complex dance movements [7].

The crucial question is that the theatre performance generally has a narrative structure, with a setup, a build, a climax and a denouement crossing all different types [18]. The process of building up the audience emotion is very important to give a clear performance structure. Therefore, in our study, we worked with stage directors to create content-related performing cues for two performances: an opera and a modern dance. Moreover, we noticed that the theatre performing cues often coordinated with multiple effects. For example, if we want to enhance the change of actor's status, we could employ obvious movement, a follow spot or sounds of footsteps to generate multiple cues, which create more impressive scenarios compared with the single cues. Thus, we divided each performance into several phases according to the performance content. In each phase we designed pairs of content-related single and multiple cues as performing stimulus when detect drops in audience engagement. We attempt to prove the hypotheses that by triggering our performing cues, the audience EEG-monitored engagement level will increase. And we are also trying to analyze how the single and multiple cues could have different influence to the engagement levels.

In our work, CryEngine™ is used to design and implement two theatre performances. We created these single and multiple cues in Flow Graph, which is a visual scripting system that is embedded in CryEngine™ Sandbox Editor. Scene, lighting, sound and special effects as stage machinery entities, could be built and set up vividly. We developed a real-time control subsystem to analyze the decreasing thresholds and establish commands to directly control the single and multiple performing cues in the Flow Graph Editor via TCP/IP networks. The system established separate threads for signal receiving and analyzing, which guaranteed the synchronization error of triggered commands and performing cues in 0.1 seconds. We also used motion capture devices (VICON™ Vantage) to record and obtain performers' original skeleton information. More implementation details of the performing cues in each performance will be described in the experiment session.

EXPERIMENT DESIGN

We designed and conducted a set of experiments including two types of theatre performance. Below we describe our experimental setup, procedure, and measurements.

Experimental Setup

We conducted a 3×1 between participants experiment, which consists two studies (two types of theatre performances). Each study includes three levels: (1) no performing cues, (2) single performing cues triggered by decreasing thresholds in EEG-measured audience engagement levels, (3) Multiple performing cues triggered by decreasing thresholds. 48 participants (24 males and 24 females) were took part in our experiment. Each condition had an equal number of participants (8 males and 8 females). The participants from different culture background and recruited from the same university. The average age was 24.4 (SD = 5.18) with a range of 19-49. All the participants had no prior experience in BCI system and their familiarity with the two theatre performances was low (M = 1.96, SD = 1.24) in the scale of one to seven. In order to create an immersive theatre performance experience, we set up the experiment in a 30 square meters testing place of our laboratory, we used a 135 degrees circular-screen projection system to present the simulated theatre performances in 3D mode. We placed the audience seat right in front of the circular-screen. Figure 5 shows the scenario of our experiment.

Experimental Procedure

The experiment consists of four main phases for each performance:

1) Introduction: Before start, the participants were asked to fill out a form for their basic information and being given a description of the experiment procedure. Then they were brought into the testing room. The researchers aided them putting on Emotiv™ to ensure good connectivity. Once the headset connection was established, the researchers helped participants put on 3D glasses and left the room. The participants started watching the simulated theatre performance on the circular-screen.

(2) Calibration: There is a 20-second calibration phase, which attempted to help audience to adapt with the device and get baseline to establish the decreasing thresholds later. In the calibration phase, the system did not employ any performing cues.

(3) Test: During this phase, the single and multiple cues were triggered according to the experimental conditions. The opera "Siegfried" and the modern dance "The Tramps of Horses" were implemented in the virtual environment for the audiences across various cultures. In the single cues condition, the single performing cues would be triggered when identified drops by monitoring the audience real-time engagement data. In the multiple cues condition, the system triggered multiple performing cues when detected drops in engagement levels. The system would continue triggered next cues right after a 15-second interval for response to the last cue without success. Due to the narrative of theatre performance, audience engagement level could be re-engaged by the performance itself. However, the difference between the performing cues and performance was that the performing cues, as theatre assistive tools, had distinct visual or auditory changes without disturbing the performance content. In no performing cues condition, the system would only detect significant drops when the decreases across the means of smoothed engagement level. In the last phase, the participants were asked to retell the content of the performance in detail as a recall task.

(4) Evaluation: At the end of the experiment, the researchers had the participants remove the headset and fill out a post-experiment questionnaire to receive subjective feedback of our system.

Objective and Subjective Measurement

The objective measurements included 10 key points with the help of stage director that measured the participants' ability to recall the details of each performance. The experimenter counted the key points that the participants mentioned, and rated a score from 0-5.

The post-experiment questionnaire included twelve questions, as a subjective measurement, it was taken by the means of a seven point rating scale (7 point is the highest score) used to measure participants' responses. It included checks on the effective of our performing cues and questions from the audience's perception of the adaptive theatre performance and whether these performing cues help to attract attention and enrich the performance content.

We utilized these measurements to confirm our algorithm could successfully identify significant drops in no performing cues condition. And we verified that the theatre performing cues enhanced the positive arousals on audience engagement in both single and multiple cues conditions.

Figure 5. An audience watches the adaptive theatre performance in 3D mode.

EXPERIMENT

"Siegfried"

We chose the classical opera "*Siegfried*" as one of the experimental performance, which is the third of the four operas that constitute "*The Ring of the Nibelung*" by Richard Wagner. We chose a five minutes scene, in which Siegfried waited for Fafner who obtained the ring and transformed himself as a dragon, to appear and fight with him. The scene consisted of three main phases: (1) the actor of Siegfried was playing a tune on his horn and trying to summon the dragon, (2) the dragon out of its cave and appeared in the dark forest at the back of the stage, (3) Siegfried fight with the dragon and stabbed in its heart.

We created pairs of single and multiple cues in each phase. One cue last 15 seconds and was obviously different from the performance content, but extracting emotional features and mapped to the scene design, lighting, sound, special effects, etc. Figure 6 shows the simulated performance compared with live performance and examples of single and multiple performing cues.

Performing Cues Design

Single Performing Cues: (1) We created sound effect to mimic a wood-bird song; Illumination of the moving brick wall. (2) The leaves blew heavily in the wind as the dragon appeared; White spotlight tracked the actor of Siegfried when he was singing. (3) A lightning streaked from sky across the dark forest; Actor interacted with the dragon in a dynamic "backward-forward" fighting move.

Multiple Performing Cues: (1) A wood-bird flew past the stage with the sound of drumming; Brick walls, rocks around the actor of Siegfried were illuminated sequentially in large-scale. (2) When the dragon was out of the cave, the ground was flaking and piles of leaves on the tree were slipping off; High-frequency color lights focused only on the actor and dragon by using white and red spotlight respectively. (3) Actor came close to the dragon amid thunder and lightning, while the back brick walls moved away from the center of the stage; when the actor fight with dragon in "backward-forward" move, red flames would be lighted on the sword and small fires were reflected on the ground.

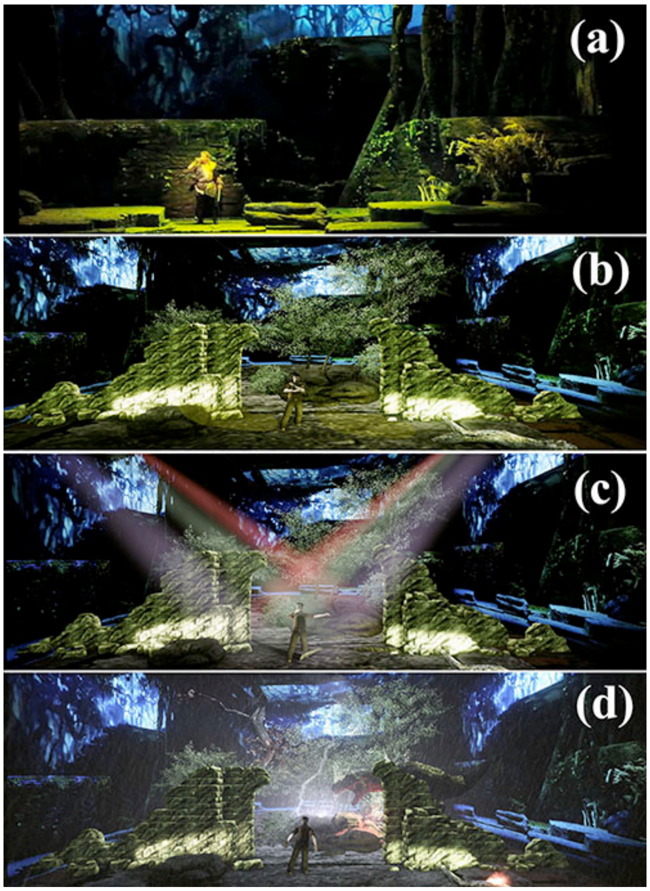

Figure 6. (a) Live performance of "Siegfried" (b) The simulated performance (c) Single cues of color lights (d) Multiple cues of actor's complex fight moves with lightning, thunder and red flames effects.

Object Results

We utilized one-way analysis of variance (ANOVA) to analyze our data from objective and subjective measurements.

To verify our system working effectively, we processed the engagement data from participants in three conditions using our algorithm to identify the times when triggered single and multiple performing cues. We analyzed the average engagement values in a 20-second timeframe before and after each performing cue. In no cues condition, the results showed that the average engagement levels 20 seconds before the triggering time were significantly higher than the average engagement levels 20 seconds after that, $F(1, 58) = 10.261$, $p = 0.002$, proving that our algorithm could correctly detecting significant decreases in audience engagement. Furthermore, we analyzed the data in single cues $F(1, 58) = 0.427$, $p = 0.515$, multiple cues $F(1, 58) = 0.326$, $p = 0.569$, conditions also in a 20-second interval before and after the triggering time, the results showed that there were no significant difference. Figure 7 showed the analysis in three levels. The results also be supported by comparing the time of status in "$S(n) = 1$" in single cues and multiple cues condition $F(1, 30) = 4.598$, $p = 0.040$, which showed that the participants obtained more positive arousals by triggering multiple performing cues than single performing cues (see Figure 9).

The recall task also supported our hypothesis that the score (in the scale of one to five) of correct answer out of 10 key points were on average 1.91 ($SD = 0.95$), 2.28 ($SD = 0.84$), and 3.37 ($SD = 0.94$) in no performing cues, single cues, and multiple cues conditions, respectively.

The result showed that the participants in multiple cues condition had better recall of the performance than in single cues condition, and participants in both of the two conditions were better than in no performing cues condition.

Subjective Results

We applied Likert scale method to the data from the questionnaire. This prediction was supported by the results that participants felt significantly clear narrative of the performance, the (no cues/single cues/multiple cues) results were on average 2.06 ($SD = 0.68$), 3.68 ($SD = 0.87$), 5.31 ($SD = 0.79$), respectively. Also, participants in single and multiple performing cues conditions reported that the performance was seamlessly embedded with the adaptive cues without distractions compared with no cues condition, the results were on average 5.25 ($SD = 0.93$), 4.93 ($SD = 0.77$), 4.87 ($SD = 0.61$). The results showed that the performing cues we designed were enabled to re-engage audience engagement, and the multiple cues had obviously better recall of performing content than in the single cues condition.

"The Tramps of Horses"

We chose modern dance "*The Tramps of Horses*" as another experimental performance, which typically represents a creative choreography with strong rhythm. We divided into four phases: (1) the dancers lined in two rows moved together with the strength and speed of their motions, (2) dancers from the back were disappeared, while seven performers were dancing creatively together with three others who playing Chinese drums, (3) the seven performers and three instrument players made the synchronous action rhythmically with a life growth background scene, (4) all the performers appeared on the stage, their complex movements built the tension as it went toward the climax at the end.

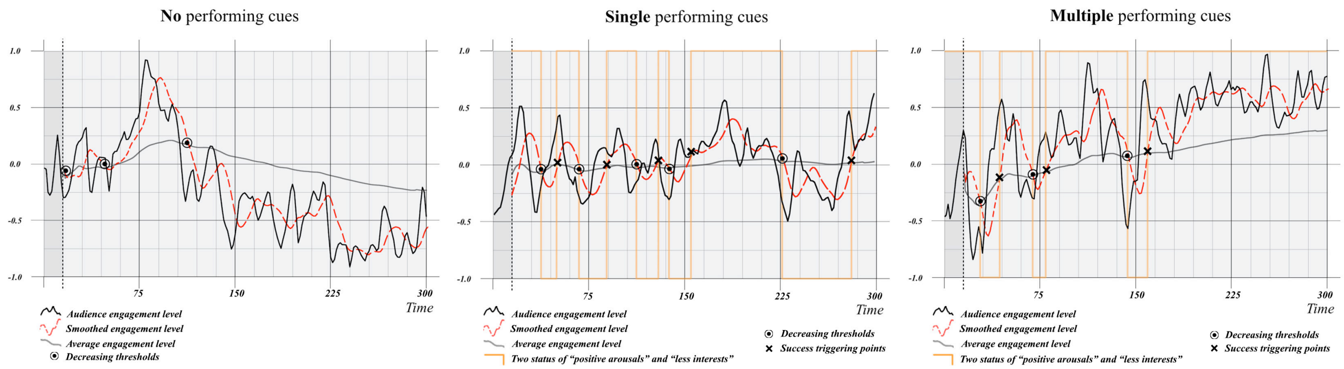

Figure 7. The analysis of three conditions in "Siegfried". Our algorithm correctly detected the decreasing thresholds in audience engagement, and regained the engagement level in a certain time. Multiple performing cues had a better effect on increasing positive arousals than single performing cues.

Performing Cues Design

Single Performing Cues: (1) A slight white spotlight with defined routine tracked performers' movements in rows. (2) A red spotlights followed the leader of dancers augmented his complex movements. (3) Sound effect of plants growing. (4) Water curtain effect; Fireworks effect around the edge of the stage.

Multiple Performing Cues: (1) A strong white spotlight traced the performers horizontally with the undulating movement of front illuminated bulks. (2) Three more performers turned somersaults across the stage with the track of individual red spotlight and then disappeared. (3) Colored lights with high frequencies in the sound of plants growing. (4) Red scattering light with water curtain fluid from top of the stage; Sparking with fireworks effect around the stage with the rotating of LED screen (See Figure 8).

Object Results

First, in no performing cues condition, the results showed that the average engagement levels 20 seconds before the decreasing thresholds were significantly higher than the average engagement levels 20 seconds after that, $F\,(1, 58) = 9.848$, $p = 0.002$, proving that our algorithm correctly detected decreases in audience engagement. Moreover, to confirm that the performing cues would successfully attract audience attention, we analyzed the data in single cues $F\,(1, 58) = 0.292$, $p = 0.590$, multiple cues $F\,(1, 58) = 0.567$, $p = 0.457$, conditions also in a 20-second interval before and after the triggering time. The evidence showed that there were no significant differences in both the single and multiple cues conditions. This also be supported by comparing the time of status in "$S(n) = 1$" in single cues and multiple cues condition $F\,(1, 30) = 1.477$, $p = 0.234$, which showed that the triggered positive arousals in both conditions were almost the same. The results had also been supported by our recall task: the score of correct answer were on average 1.96 ($SD = 0.92$), 3.09 ($SD = 0.84$), and 3.56 ($SD = 0.85$) in the no performing cues, single cues, and multiple cues conditions, respectively.

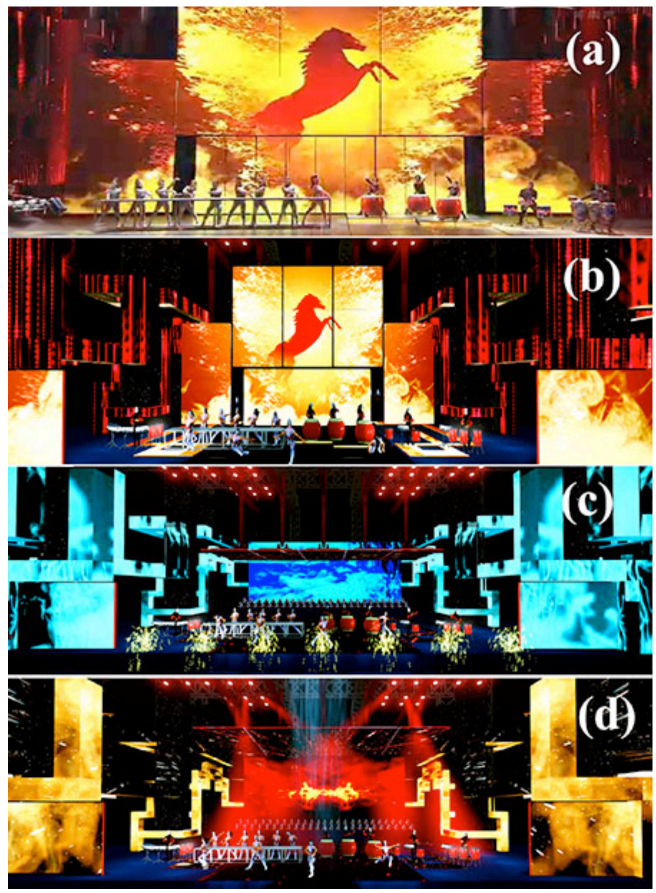

Figure 8. (a) Live performance of "The Tramps of Horses" (b) The simulated performance (c) Single cues of fireworks effect (d) Multiple cues of water curtain and red scattering light.

These results showed that in both single and multiple cues conditions, the participants had better recall of the performance content than no performing cues condition.

Subject Results

We also investigated that whether the participants involved in the multiple cues condition felt more attracted than in the single cues condition. The results showed that there were no obvious difference between the two conditions, the results were on average 4.37 (*SD* = 0.80), 4.81 (*SD* = 0.91). It showed that the performing cues we designed were enabled to re-engage audience engagement, however there were no big distinctions of effects between the single cues and multiple cues conditions.

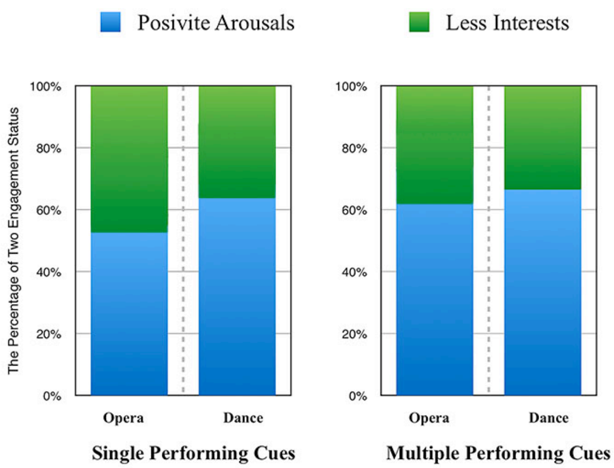

Figure 9. The percentage of two engagement status for averaging all participants in the single and multiple cues conditions of two types of theatre performance.

DISSCUSSION

The experiment showed that we could successfully detected significant decreasing thresholds by using our algorithm, and proved our hypothesis that the use of adaptive theatre performing cues could regain audience engagement in real-time across different types of theatre performances. Our results supported the hypothesis that by using performing cues the participants had better recall of the performance content.

Despite the positive results from our research, we investigated whether the participants would positively rate in multiple cues condition than in single cues condition, the data showed that in opera experiment the audience felt more attracted by triggering multiple performing cues than single performing cues, however there were no significant differences between the two conditions in the experiment of modern dance. This was because that modern dance usually has a fast-paced narrative rhythms, the detection of decreasing thresholds in audience engagement would only happened in certain moments. This evidence showed that the performing cues might have different impacts on attracting audience attention according to various performance types.

We also found that most of the participants did not felt been interrupted during the virtual theatre performance with the embedded performing cues. Our results had proved that the content-related performing cues would re-engage audience engagement unconsciously based on EEG-measured data while keeping the performance rhythm smooth. However, we have not found any significant difference between the male and female participants, but a few females mentioned that they were more impressed by the dynamic changes of lighting and special sound effects. These results lend credence to the idea that performing cues could improve audience engagement, which could be a positive factor in the future of theatre performance design from the audience perception.

Due to the limitation of simulated an immersive theatre environment in our laboratory, some complex features, for example performers' facial expressions, might need high-accuracy motion capture device to create more vivid scenes. While our system achieved its predicted goal of increasing audience attention by monitoring their engagement data in real-time and triggering performing cues when detected drops in audience engagement levels. Our engagement values were based on EEG signals, which were easily to be affected by other signals such as muscle artifacts due to the limitation of the EEG technology. Although we employed filters to remove noise signals, we still need to validate the presented engagement values were excluded irrelevant signals.

CONCLUSION AND FUTURE WORK

To successfully adjust performing content from audience perception into theatre performance in real-time, the system should be able to correctly measure and response to audience engagement state. In our research, we created an adaptive system, which enhances the theatre performance experience by real-time monitoring audience engagement levels from EEG data and employs performing cues that stage designers could use to regain audience attention when detecting significant decreases. We found that the adaptive theatre performance with embedded performing cues could improve the audience recall ability across various types of performances unconsciously. We hope our research serves as a springboard for further investigation into the field of performing arts to employ digital techniques, which could aid the design of theatre performance to create more fluid interactions with audience.

In future work, we should think about the following questions: How could our system be improved to integrate EEG monitoring with other biometric measures such as heart rate, blood pressure to improve the adaptability? Generally, the theatre performances were presented for the crowds, how could we assess the effects of social interaction during an adaptive performance to verify the effectiveness? Our future work will seek to answer these questions and towards understanding of various performing cues affect audience response across types of performances to improving our system.

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