VIRTUAL SPACE GENERATION METHOD DRIVEN BY INTEGRATED MULTI-SENSORY FEEDBACK DATA

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Abstract. Ergonomics and human factors have gradually taken center stage in generative design. This study investigated a topic that has not received enough attention: using generative methods to couple visual and auditory aspects in space design. Twenty participants were recruited for two sequential experiments to investigate the workflow of generating virtual space with auditory and visual inputs. First, six genres of music were played to arouse their emotion. To create the fitness function for the genetic algorithm, corresponding EEG data related to meditation and attention was gathered. Subsequently, the genetic algorithm optimized the VR device's spatial structure to obtain a value similar to the initial experiment. Thus, with an algorithm to integrate the EEG data, space and music can be coupled and trigger similar emotional states. The results showed considerable emotional differences between music genres in EEG data and questionnaires. It showed the potential of this workflow to generate stylish space coupling with distinct music. This study innovatively integrates auditory and visual elements, developing an interactive and generative design method with multi-sensory input. It also offers insights into enhancing the immersive experience of wearable VR devices.

Keywords. EEG Intervention, Generative Design, Music Evaluation, Spatial Perception, Emotional Regulation, Virtual Reality

1. Introduction

Space is valued for its diversity of emotions and atmospheres and its dimensions and

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forms. People's behavior, cognitive function, and physical and mental health are all correlated with their physical surroundings. Extensive research has looked into the connection between space design components and the psychological well-being of people through the use of quantitative test methods. For example, the workplace environment is associated with increased productivity and efficiency (Ergan et al., 2018). Furthermore, studies have discovered that architectural elements, such as fence color, environmental light, item outlines, and building style, can influence people's perceptions and sentiments(Huang & Xu, 2009).

Researchers have been assessing architectural environments since the 1980s using electroencephalography (EEG), giving them additional insight into how people perceive environments and architectural features (Hu & Roberts, 2020). Moreover, studies have demonstrated that EEG signals are capable of measuring people's emotions, such as stress and relaxation levels (Katmah et al., 2021; Shabbir Alam et al., 2022). To further analyze people's feelings in real life, researchers have integrated Virtual Reality (VR) technology and EEG signals in mock tests (Chen et al., 2020; Hu & Roberts, 2020). VR provides a more immersive experience than 2D images. Furthermore, parametric models can be rendered instantaneously in VR, allowing for a real-time preview of changes to the parameters. However, while EEG technology is utilized to analyze space objectively, prior research on spatial optimization mostly focused on visual-spatial aspects, such as wall color, window openings, and ceiling height(Ergan et al., 2018; Kim et al., 2021). Using EEG and VR technology, we plan to integrate the often overlooked auditory components into the generative spatial design, merging the visual and auditory senses.

2. Research Aim

We aim to establish a link between music, space, and emotion using EEG technology. By investigating generative design techniques that incorporate both visual and auditory elements, we also envision to open up new possibilities for future research into the integration of multimodal stimuli in generative design. Figure 1 illustrates the workflow of our research and our envision.

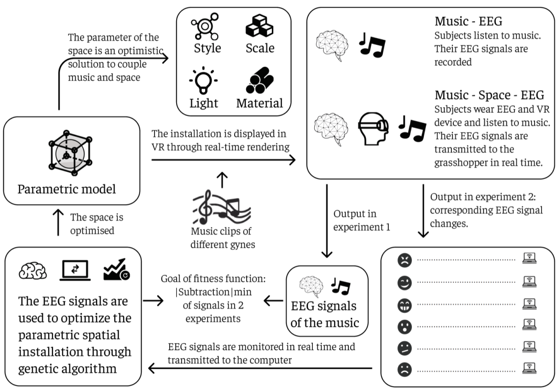


Figure 1. Research workflow and envison

3. Method

3.1. HARDWARE AND SOFTWARE PLATFORM

The working platform is divided into two distinct parts: the hardware platform and the software platform, as shown in Figure 2.

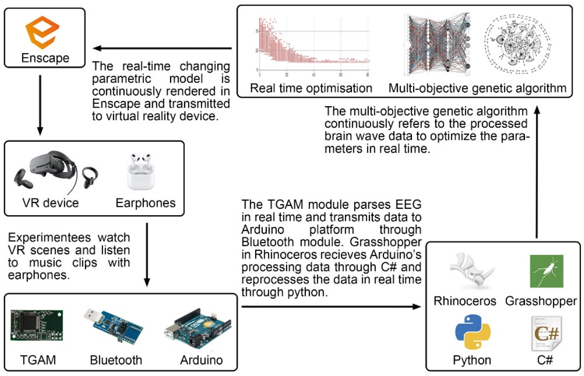


Figure 2. Hardware and software platform

On the hardware platform, using a Bluetooth module, the TGAM module transmits the raw data of five waveforms (α, β, γ, θ, δ) and the calculated meditation and attention values(meditation values mainly represent a sense of calmness; attention values represent focu) to the Arduino board.

On the software platform, the Arduino IDE facilitates the transfer of unprocessed EEG data from TGAM to the computer's serial port.The C# plugin in Grasshopper is utilized for data reception, while the Python plugin performs real-time data processing within it. As the subjects observe the VR scene generated in real-time with Enscape(a rendering software wth an interface to VR devices), the changing EEG data acquired in real-time is sent to Wallacei(a multi-objective genetic algorithm). The algorithm will constantly improve and generate the parametric model until it meets the optimization goals.(Zhang et al., 2022)

3.2. EXPERIMENTAL PREPARATION

We recruited 20 healthy volunteers (8 males and 12 females, aged between 20 and 40) to participate in the experiment. Curtains were drawn at the start of the experiment in the quiet laboratory setting to reduce interference from external light. Watching the experiment unfold, the researchers sat in a way that had no effect on the experimenters. Prior to the experiment, the subjects wore the TGAM module, VR glasses, and in-ear noise-canceling Bluetooth headphone.The experiment started once the participants got acclimatized to the virtual reality settings. The subjects sat in front of the computer during the experiment, and the researcher could view the images on the screen through their VR glasses.

4. Experimental Design

The experiments are divided into two parts. First, the subjects' EEG data were monitored and recorded while listening to six music genres. Following that, participants had to answer a questionnaire on their emotions related to the music. In the second experiment, a genetic algorithm was built using the average meditation and attention values derived from the first trial.

4.1. EXPERIMENT 1

In experiment 1, subjects wore headphones and a TGAM EEG module. From the CAL500 dataset (Turnbull et al., 2008), six musical genres were chosen: pop, jazz, rock, country, electronic, blues, and electronic music. There were six experiments in all, with each musical genre trimmed and merged into 300-second segments. Their EEG data was recorded when the subjects listened to a certain kind of music. They then answered a questionnaire to assess their emotions regarding the music.

We measure emotions in that questionnaire using a model based on valence and arousal, which interprets emotions as a linear combination of two variables, placing them on a circular model (Russell, 1980). The music was evaluated using a Likert scale for valence (-2 to 2, with -2 indicating extreme unpleasantness and 2 indicating extreme pleasantness) and arousal (-2 to 2, with -2 indicating very low arousal and 2 indicating very high arousal).

To process data, we extracted the average meditation and attention values from subjects who listened to the music for the second experiment. Therefore, we selected music with greater convergence to ensure precision. According to studies on the relationship between musical genres and emotions, certain musical genres—like pop music—have more widely distributed valence distributions, which lead to more erratic emotional responses. In contrast, other genres are more predictable. And music within the same genre tends to have more similar arousal levels(Eerola, 2011). We evaluated their convergence by analyzing questionnaire responses and EEG data.

Based on the EEG data of 20 subjects listening to six genres of music, we calculated the overall average meditation values for each genre of music and their respective standard deviations (as shown in formula 1 and formula 2, where n represents the number of subjects). The calculation for Attention follows the same principle.

$$\text{Average}_{\text{Meditation}} = \frac{\sum_{n=1}^{20} Average_{meditation_n}}{20} \tag{1}$$

$$\sigma = \frac{\sqrt{\sum_{n=1}^{20} \left(Average_{meditation_n} - \text{Average}_{\text{Meditation}}\right)^2}}{20} \tag{2}$$

4.2. EXPERIMENT 2

The second experiment consists of two parts: the main experiment and the post-experiment. The main experiment consists of subject training, equipment calibration, and listening sessions for country and rock music, interspersed by a rest period. The post-experiment includes a questionnaire interview.

Prior to the start of the experiment, subjects adapted to the wearable device and VR environment to yield more precise EEG data (Cui et al., 2022; Sun & Li, 2020). They then observed how the music altered the space in virtual reality settings. Every five seconds, the parameters of the space, such as its degree of openness and light colors, were altered. To determine the fitness of the space at that particular moment, Wallacei's genetic algorithm processed the EEG data collected during these 5-second intervals. The experiment terminated after 20 iterations. The experiments for country and rock music were conducted separately.

The space's openness degree, light, and color significantly influence people's experience. We emphasized these varying elements when choosing our parametric model. Using Grasshopper, we created a spatial structure controlled by two variables. Our selected variables are the components' opening angle and the light's color (Ergan et al., 2018). As illustrated in Figure 3, the opening angle range is 0-135°. At 0°, the structure allows minimal light entry, making it almost impossible for the subject inside to see the external environment. At 135°, the structure permits maximum light entry, allowing the subject to see the outside world.

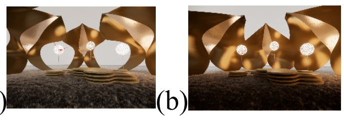
(a) (b)


Figure 3. Model at various opening angles(a)opening angle at 135° (b)opening angle at 0°

HSL has three main components: hue, saturation, and lightness, representing the color's hue, vividness, and intensity. As the three color components—red, green, and blue—have varying degrees of sensitivity in the human eye, we utilize HSL rather than RGB when selecting the parameters.(Ajmal et al., 2018).Considering computational power, we selected 12 representative hues from the HSL color model for our experiment. These hues are: 0°, 30°, 60°, 90°, 120°, 150°, 180°, 210°, 240°, 270°, 300°, and 330°, along with 11 values each for saturation and lightness, ranging from 0 to 100 in increments of 10. Conventional primary and secondary colors are separated by 60 degree intervals on the HSL color wheel. Red is at 0°, yellow at 60°, green at 120°, cyan at 180°, blue at 240°, and magenta at 300°.

Our research aims to couple music and space using EEG signals. As a result, we decided to minimize the variation between the average meditation and attention values that were recorded in the two studies as our optimization objective. Formula 3 is as follows. $\text{Average}_{\text{Meditation1}}$ represents the average meditation value for all the subjects listening to a single genre of music in the first experiment.

Average$_{Meditation2}$ represents the average meditation value for each subject listening to the corresponding genre of music from the first experiment in the changing virtual space of the second experiment. Difference$_{Meditation}$ represents the absolute value calculated after subtraction of Average$_{Meditation1}$ and Average$_{Meditation2}$. In multi-objective genetic algorithms, a lower Difference_Meditation indicates higher fitness. The calculation for Attention follows the same principle.

In calculating each Average value, we discard the EEG data from the first and last seconds, using the average of the remaining EEG values as the reference for Average$_{Meditation}$ and Average$_{Attention}$. Formula 4 is as follows. In the formula below, t0 and t1 represent the moments 1 second after the start and 1 second before the end of each scene change. The calculation for Attention follows the same principle.

$$\mathrm{Difference}_{\mathrm{Meditation}} = |\mathrm{Average}_{\mathrm{Meditation}_1} - \mathrm{Average}_{\mathrm{Meditation}_2}| \tag{3}$$

$$\mathrm{Average}_{\mathrm{Meditation}} = \frac{\int_{t0}^{t1} Meditation\, dt}{t1 - t0} \tag{4}$$

On the choice of experimental time, the individuals may become fatigued if the length is increased to 25 generations (more than 20 minutes). Therefore, we decided to run 20 generations of the experiment, changing the scene ten times each generation for a total of about 18 minutes.

5. Results

5.1. EXPERIMENT 1 QUESTIONNAIRE

Figure 4 shows the evaluations of six music genres by 20 subjects. Four quadrants comprise 120 findings on a circular emotional model. Assessments of Rock music tend to be spread in the first and second (excited - nervous) quadrants, but assessments of Country music are mostly found in the first quadrants (elated - excited). Electric music evaluations are mostly found in the first and fourth quadrants (serene - excited). Rock music obtains fewer neutral assessments (valence=0, arousal=0), while Pop, Jazz, and Blues music receive more.

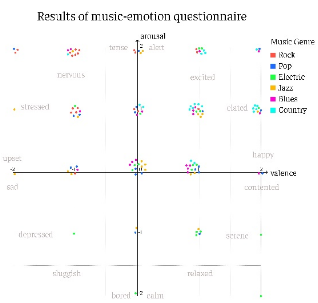


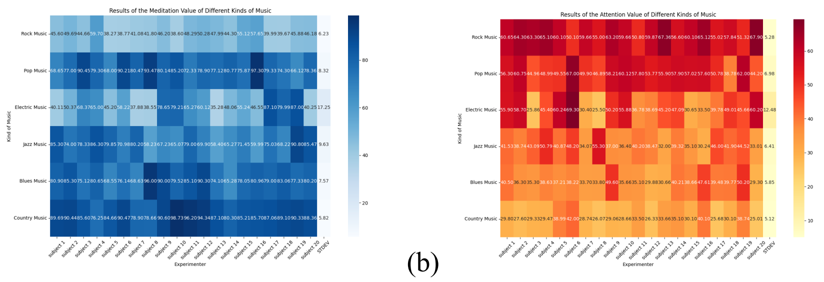
Figure 4. Results of questionnaire

We counted the average values and standard deviations of the evaluations of six types of music by 20 subjects. The data suggests that Rock music has the highest average arousal and the lowest average valence, while Country music shows the lowest average arousal and the highest average valence. Meanwhile, they have minor standard deviations.

5.2. EXPERIMENT 1 EEG

Heatmaps showing the meditation and attention values for twenty subjects while they listened to six different kinds of music are shown in Figure 6. Blue stands for meditation values, and red for attention values; the higher the value, the darker the color. Of all the subjects, rock music has the greatest average attention value, followed by pop music, and country music has the lowest. Country music has the highest meditation values, followed by Blues and Pop music, with Rock music the lowest.

Furthermore, Country and Rock music have minor standard deviations in attention values, at 5.12 and 5.28, respectively, and minor standard deviations in meditation values, at 5.82 and 6.23, respectively. Electric music has the highest standard deviations with attention and meditation standard deviations of 12.48 and 17.25, respectively, which are more than twice as high as those of the other music genres. It implies that whereas country and rock music elicit more predictable emotions, electric music elicits more complicated emotions. In general, listeners of country music tend to be more at ease and pay less attention, whereas listeners of rock music tend to be more tense and pay more attention.



(a) (b)

Figure 6. Heatmaps of the meditation and attention values for 20 subjects while listening to six types of music: (a)meditation values; (b)attention values

In conclusion, Rock and Country music triggers listeners' most stable and distinct feelings. Therefore, these two genres were chosen for the main experiment.

5.3. EXPERIMENT 2

Table 1 shows six of the more optimal results from the Country music experiment (the six with the smallest sum of $\text{Difference}_{\text{Meditation}}$ and $\text{Difference}_{\text{Attention}}$). The opening angles are between 0-60°, mostly at 0°. The hues are between magenta and yellow. Saturation is evenly distributed between 40-80, and lightness is between 30-80.

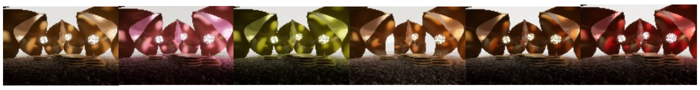
Subject	1	2	3	4	5	6
Opening angle	0	0	0	60	0	0
H	30	330	60	30	30	0
S	40	80	60	50	70	50
L	60	80	40	50	30	40
Average attention	30	32	29.5	27.5	33.5	35
Average meditation	90.5	92	87	90	87	85
Model						

Table 1. Optimal results from the Country music experiment

Table 2 shows six of the more optimal results from the Rock music experiment (the six with the smallest sum of Difference_Meditation and Difference_Attention). The spatial openness is more unevenly distributed, with 60% at 135° and the rest at 120°, 60°, and 0°. Hues are concentrated between magenta and yellow, with one green. Saturation is evenly distributed between 70-90, averaging higher than the results for Country music. Lightness is evenly distributed between 30-60, averaging lower than the results for Country music.

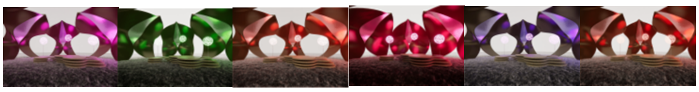
Subject	1	2	3	4	5	6
Opening angle	135	60	135	0	135	120
H	300	120	0	330	270	0
S	80	70	80	70	80	90
L	50	30	60	50	40	40
Average attention	60.5	62	62.5	64.5	59	57.5
Average meditation	45	42	41.5	47	46.5	44
Model						

Table 2. Optimal results from the Rock music experiment

We asked the individuals to complete a questionnaire survey following the main experiment to find out how they felt the music and the space were congruent. Two respondents thought it was congruent, two felt it was average, two felt it was not congruent, and none felt it was extremely not congruent. Of the participants, fourteen thought it was very congruent. Overall, our participants reported that the music and the space were highly congruent, proving the efficacy of our methodology.

6. Conclusion and Discussion

This study combined visual and audio elements with EEG data for generative spatial design optimization. We confirmed that different music genres trigger different emotions by measuring subjects' emotions to music through questionnaires and EEG data. Taking Country and Rock music as examples, in the second spatial optimization experiment, we optimize the openness of space and colour of light by lowering the absolute differences in EEG values between the two experiments, leading to distinct optimization results for the two music genres.

Still, our research has limitations. It is possible that music with more significant standard deviations in evaluation will not yield well-predicted results when the fitness function is established using average values. Additionally, we did not choose participants in larger and more significant numbers across a wider age range.

In the future, we plan to expand our research to include more sensory factors, such as olfaction and gustation, and to broaden the range of spatial parameters. To obtain more accurate results, we plan to combine machine learning with increasingly sophisticated devices for quantitative analysis. After significant data input and model training, we can predict the music and spatial parameters most likely to trigger particular emotional or cognitive states by examining participants' EEG representations and the music and spatial characteristics triggering them with machine learning. Furthermore, personalized models can be created to forecast which music genres or settings are most likely to elicit desired emotional or cognitive states in specific individuals by using machine learning to analyze individual reactions to music and space.

In application scenarios, we envision using consumer EEG and VR devices to create interactive virtual spaces with music for meditation training and cognitive state regulation. Real-time adjustments and changes are made to the virtual spaces according to the user's desired mental state, desired music selection, and current EEG data. Additionally, our methodology may be used for the creation of stylized music spaces, offering a quantitative framework for choosing spatial elements.

Our overall goal is to improve multimodal design by creating a multisensory virtual space generative design approach based on EEG, which incorporates tactile, olfactory, and gustatory factors in addition to auditory elements. This approach has potential development prospects in both virtual and real space design.

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