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ANALYSIS OF THE CORRELATION BETWEEN BRAIN AND SKIN REACTIONS TO DIFFERENT TYPES OF MUSIC

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Abstract

Evaluation of the correlation among the activities of various organs is an important research area in physiology. In this paper, we analyzed the correlation between the brain and skin reactions in response to various auditory stimuli. We played three different music (relaxing, pop, and rock

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music) to eleven subjects (4 M and 7 F, 18–22 years old) and accordingly analyzed the changes in the complexity of Electroencephalogram (EEG) and Galvanic Skin Response (GSR) signals by calculating their fractal exponent and sample entropy. A strong correlation was observed among the alterations of the complexity of GSR and EEG signals in the case of fractal dimension ($r = 0.9971$) and also sample entropy ($r = 0.8120$), which indicates the correlation between the activities of skin and brain. This analysis method could be further applied to investigate the correlation among the activities of the brain and other organs of the human body.

Keywords: Skin; GSR Signals; Brain; EEG Signals; Fractal Dimension; Sample Entropy; Complexity.

1. INTRODUCTION

Skin as the cover of the body reacts to external changes around us. For instance, we feel the cold with our skin. For years, several works have been devoted to investigating human skin reactions, mainly for emotion recognition[1,2] and in response to external stimuli.[3–5] It is known that the human skin as the body's cover is controlled by the brain through the nervous system. Although the nature of this control, which is performed through a high degree of complexity, is not fully understood,[6] however, an important category of work is to quantify the correlation among the reactions of skin and brain in different conditions.

In this study, we focus on analyzing the correlation between the brain and skin activities. According to the literature, some researchers have simultaneously analyzed the reaction of the brain and skin in different conditions.[7–10] Since music affects the human skin,[11] studying the correlation between brain and skin in auditory stimulation is very important. Therefore, in this paper, for the first time, we discuss the correlation between brain and skin reactions while participants listen to different music.

Since the brain and skin activities, which are quantified using EEG and GSR signals, have complex structures, we utilized fractal theory to evaluate the correlation among the brain and skin reactions to auditory stimuli. Fractals are objects (1D, 2D, or 3D) that show self-similarity or self-affinity. We can observe how different segments of a self-similar fractal object have a geometrical relationship to each other. However, self-affine fractals behave differently, and we cannot see any relationship among their different parts due to their different scaling exponents in various directions.[12] Therefore, EEG and GSR signals are categorized as self-affine fractals. Fractal exponent is the principal exponent to quantify the complexity of fractals. In general, for a fractal object, the fractal dimension satisfies the following Szpilrajn inequality:

$$F \geq D, \tag{1}$$

where F and D represent the fractal dimension and topological dimension (Euclidean dimension) of the object, respectively.

Many works have investigated complex structures of various physiological signals using fractal theory.[13–17] Similarly, many works have analyzed the EEG signals due to external stimulation using fractal theory. The studies that evaluated the effect of auditory,[18,19] electrical,[20,21] and visual[22,23] stimuli on EEG signals, can be stated. However, the application of fractal theory in the analysis of GSR signals was limited. In Ref. 10, we analyzed the skin's reaction to different odors, and in Ref. 24, the authors identified the drivers' distraction by evaluating their GSR signals.

In this work, we also chose sample entropy to evaluate the complexity of recorded signals. In fact, we verified the result of the fractal analysis by computing their sample entropy. Sample entropy has been utilized extensively to analyze the complexity of various types of physiological signals. Specifically, we can mention many works that used sample entropy to analyze the EEG signals.[25–27] However, the application of sample entropy in GSR signals analysis has been very limited.[28]

As previously mentioned, no reported study has focused on the analysis of the correlation between skin and brain reaction due to auditory stimuli. Therefore, in this paper, we applied fractal theory and sample entropy to EEG and GSR signals to evaluate how the alterations of these complex signals are coupled with the changes in the auditory stimuli.

2. METHOD

We evaluated the correlation between the reactions of the brain and skin in auditory stimulation. We utilized the fractal theory to quantify the complexity of EEG and GSR signals. Fractal exponent reflects the complexity; an object with greater complexity has a bigger fractal exponent.

We utilized the box-counting fractal dimension to quantify the complexity of EEG and GSR signals. The box-counting algorithm covers the object with same-size (ε) boxes and accordingly counts their number (N). This process is repeated in further levels by changing the box size at each level. The fractal dimension is computed as

$$F = \lim_{\varepsilon \to 0} \frac{\log N(\varepsilon)}{\log 1/\varepsilon}. \tag{2}$$

Equation (2) in the general form is formulated as[29]

$$FD_h = \lim_{\varepsilon \to 0} \frac{1}{h-1} \frac{\log \sum_{j=1}^{N} z_j^h}{\log \varepsilon}, \tag{3}$$

where h is the order and z_j indicates the probability

$$z_j^h = \lim_{t \to \infty} \frac{t_j}{T}, \tag{4}$$

where T represents the total period of the signal.

We also utilized sample entropy to quantify the complexity of EEG and GSR signals in different music stimulation. Sample entropy is similar to the approximate entropy but is independent of the length of data. If we consider a signal in the form of $\{y(1), y(2), \ldots, y(n)\}$ with a constant interval of α, we define a template vector of length k in the form of $W_k(i) = \{y_i, y_{i+1}, y_{i+2}, \ldots, y_{i+z-1}\}$, and the distance function $d[W_k(i), W_k(j)] (i \neq j)$ is to be Chebyshev distance. Then, the sample entropy (SamEn) is formulated as[30]

$$\text{SamEn} = -\log \frac{A}{C}. \tag{5}$$

Considering ε as the tolerance ($0.2 \times$ standard deviation of data), A stands for the number of template vector pairs that

$$d[W_{k+1}(i), W_{k+1}(j)] < \varepsilon. \tag{6}$$

Besides, C stands for the number of template vector pairs that

$$d[W_k(i), W_k(j)] < \varepsilon. \tag{7}$$

We chose three music as auditory stimuli in this study. These auditory stimuli include relaxing music, pop music, and rock music. In fact, choosing different types of music enabled us to evaluate the correlation among the complexities of EEG and GSR signals.

We played each music for subjects and then investigated the correlation between EEG and GSR signals by calculating their fractal exponent and sample entropy.

3. DATE COLLECTION AND ANALYSIS

This paper was approved by Monash University (# 18267). The experiment was run on eleven healthy participants (4 M, 7 F, 18–22 years old) after they gave their consent. Participants did not drink alcoholic/caffeine beverages within 48 h before sitting for the experiment.

As shown in Fig. 1, we attached the EMOTIV EPOC EEG device to the subject's scalp. It contains 14 recordings and 2 reference electrodes. We also attached the Shimmer GSR device to the right hand of the subjects, and its two electrodes were mounted on the subject's fingers. We recorded EEG and GSR signals, respectively, at 128 Hz and 51.2 Hz. We used a computer speaker to play each music to subjects at 50 dB.

Initially, we recorded EEG and GSR signals during rest for one minute. Then we, respectively, played "Zen", "Happy", and "My life" music as relaxing, pop, and rock music (each music for one minute) to the subjects and recorded their EEG and GSR signals. One-minute rest was given to participants between different stimulations. The experiment has been repeated in another session for all

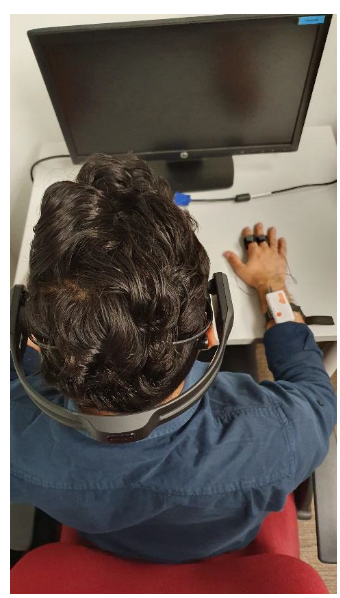

Fig. 1 The setup of the experiment.

participants. We should note that the EEG device had some poor connection (or disconnected) during the data collection in four periods, and therefore, we excluded those recorded data from the analysis.

After removing the DC offset, we filtered EEG signals using Butterworth band-pass filter at 1–40 Hz. We also denoised GSR signals at 20 Hz cut-off frequency. We checked the filtered versus raw signals to ensure the quality of filtering. After that, we calculated the fractal exponent and sample entropy of filtered signals. We used boxes with the sizes of $\frac{1}{2}, \frac{1}{4}, \frac{1}{8}, \frac{1}{16}, \ldots$ in running the box-counting algorithm. All steps of data analysis were conducted in MATLAB R2019a (MathWorks, USA).

We compared the complexity of EEG signals (and GSR signals) among various conditions by conducting the posthoc test. Besides, the effect sizes (Cohen's d) were computed to analyze the effect of different music on the alterations of the complexity of EEG and GSR signals. We examined the correlation among the alterations of complexity EEG and GSR signals by calculating the Pearson correlation coefficient. The significance level of 0.05 was chosen for statistical analyses.

4. RESULTS

The presented results are based on the average of recorded data from all channels for all participants in both recording sessions. The changes in the fractal exponents of EEG signals are shown in Fig. 2. Error bars indicate the standard deviation.

As Fig. 2 demonstrates, the EEG signals' fractal exponent increased due to the application of first music to the subjects. After that, by moving from relaxing to pop and rock music, the fractal exponent of EEG signals reduced. Therefore, we can state that initially, the complexity of EEG signals increased and then decreased. The initial increase of the EEG signals' complexity is due to the sudden change in the brain's activity because of external stimulation.

Comparing the fractal exponents among the various conditions (Table 1) demonstrates that in general, rock music caused a more significant alteration in the EEG signals' complexity compared to pop music, which itself caused more significant changes in the EEG signals' complexity compared to relaxing music. Here, we should note that, in this study, we look for the correlation between the alterations of EEG and GSR signals, not the significance of their alterations due to stimulation. Besides, the calculated values of Cohen's d in this table indicate that by moving from relaxing to pop and rock music, the impact of the music on the alterations to the EEG signals' complexity increased.

Figure 3 illustrates the alterations of the fractal exponent of GSR signals. Error bars indicate standard deviation.

Table 1 Comparing the Fractal Exponents of EEG Signals.

Pairwise Comparison	p-Value	Cohen's d
Rest versus relaxing music	0.9668	−0.1470
Rest versus pop music	0.9935	0.0887
Rest versus rock music	0.6603	0.3380
Relaxing versus pop music	0.8867	0.2357
Relaxing versus rock music	0.3913	0.4574
Pop versus rock music	0.8070	0.2687

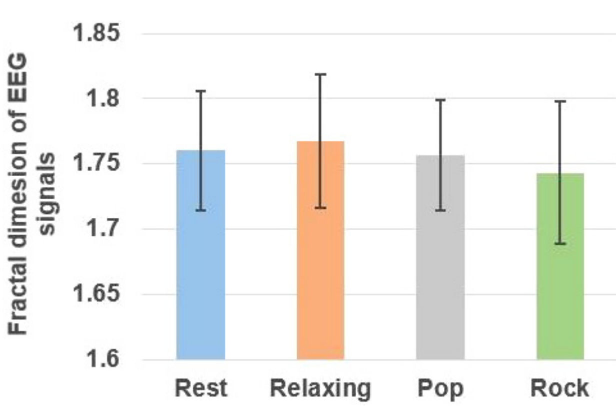

Fig. 2 The fractal exponent of EEG signals.

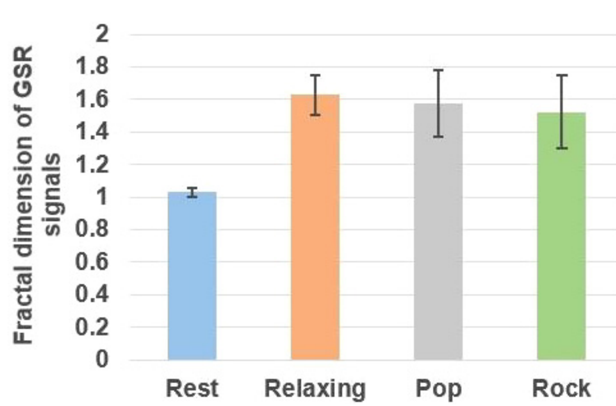

Fig. 3 The fractal exponent of GSR signals.

As can be observed, the GSR signals' fractal exponents increased due to the application of relaxing music and then decreased as we moved to pop and rock music. The initial increase of the GSR signals' complexity is due to the sudden change in the skin's activity because of external stimulation. Therefore, the alterations of the GSR signals' complexity have a similar trend with the changes in EEG signals' complexity in Fig. 2. Besides, the calculated Pearson correlation coefficient of 0.9971 reflects a strong correlation between the alterations in the EEG and GSR signals' complexities when subjects listened to music.

Multiple comparisons of the fractal exponents of GSR signals in Table 2 demonstrate that by moving from relaxing to pop and rock music, the alterations in the complexity of GSR signals become more significant. Besides, the effect sizes in this table demonstrate that rock music had the largest effect on the fractal exponent of the GSR signals.

Qualitatively comparing the effect sizes between Tables 1 and 2 indicates the greater influence of music on changing the complexity of GSR signals than EEG signals from the rest condition. This finding can be referred to as the activity of the brain versus skin during rest. It is known that the skin is less active than the brain during rest (the brain is engaged with different processing even in rest condition), and therefore, listening to music increased its activity greater than the brain. Therefore, stimulation of subjects with music caused greater alterations in the activity of the skin than the brain.

Figure 4 illustrates the sample entropy of EEG signals in rest and stimulations. Error bars indicate standard deviation.

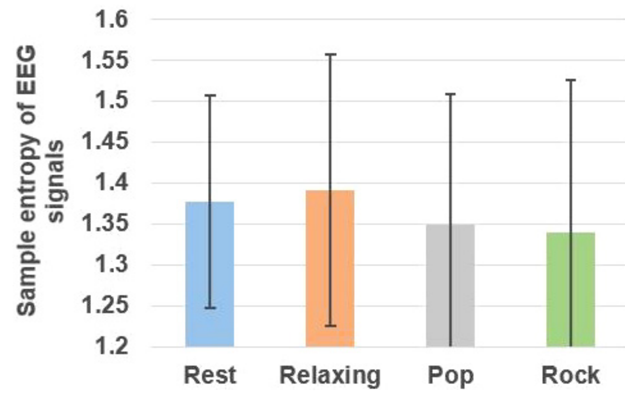

Fig. 4 The sample entropy of EEG signals.

As Fig. 4 demonstrates, the EEG signals' sample entropy increased due to the application of first music to the subjects. After that, by moving from relaxing to pop and rock music, the sample entropy of EEG signals decreased. Therefore, the complexity of EEG signals increased and then decreased. Comparing this figure with Fig. 2 indicates that the results of sample entropy verify fractal analysis findings.

Multiple comparisons from the Tukey test in Table 3 demonstrate that by moving from relaxing to pop and rock music, the changes of sample entropy of EEG signals become more significant. As was mentioned previously, the in-significant alterations of the complexity of EEG signals between different conditions are not considered in this research since we are looking for the correlation between the alterations of EEG and GSR signals, not the significance of their alterations due to stimulation. Besides, the values of Cohen's d in this table

Table 2 Pairwise Comparison of Fractal Exponents of GSR Signals.

Pairwise Comparison	p-Value	Cohen's d
Rest versus relaxing music	0.0000	−6.8699
Rest versus pop music	0.0000	−3.7458
Rest versus rock music	0.0000	−3.1163
Relaxing versus pop music	0.7135	0.3288
Relaxing versus rock music	0.1842	0.5890
Pop versus rock music	0.7440	0.2360

Table 3 Pairwise Comparison of Sample Entropy of EEG Signals.

Pairwise Comparison	p-Value	Cohen's d
Rest versus relaxing music	0.9913	−0.1005
Rest versus pop music	0.9407	0.1940
Rest versus rock music	0.8708	0.2340
Relaxing versus pop music	0.8301	0.2655
Relaxing versus rock music	0.7274	0.2979
Pop versus rock music	0.9973	0.0549

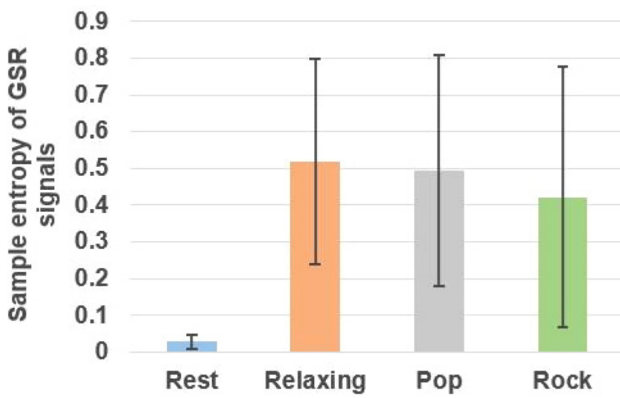

Fig. 5 The sample entropy of GSR signals.

indicate that rock and relaxing music, respectively, have the largest to smallest effect on alterations to the complexity of EEG signals.

Figure 5 shows the alterations of the sample entropy of GSR signals in rest and stimulations. Error bars indicate standard deviation.

This figure shows that the sample entropy of GSR signals increased due to the application of relaxing music and then decreased as we moved to pop and rock music. In fact, this result is similar to the result of fractal analysis in Fig. 3. On the other hand, Figs. 4 and 5 show similar trends for the EEG and GSR signals' sample entropy. Besides, the calculated Pearson correlation coefficient of 0.8120 reflects a strong correlation between the alterations in the EEG and GSR signals' complexity when subjects listened to different music. Therefore, the analysis of sample entropy verified the result of fractal analysis.

Multiple comparisons of the sample entropy of GSR signals in Table 4 demonstrate that by moving from relaxing to pop and rock music, the alterations in GSR signals' complexity become more significant. Besides, the effect sizes in this table indicate that rock music had the biggest effect on the sample entropy of the GSR signals.

Table 4 **Pairwise Comparison of the Sample Entropy of GSR Signals.**

Pairwise Comparison	p-Value	Cohen's d
Rest versus relaxing music	0.0000	−2.4806
Rest versus pop music	0.0000	−2.0929
Rest versus rock music	0.0001	−1.5683
Relaxing versus pop music	0.9915	0.0843
Relaxing versus rock music	0.6836	0.3016
Pop versus rock music	0.8283	0.2126

Therefore, according to the results, the changes in the GSR and EEG signals' complexity are coupled; as we shift between different stimuli, the fractal exponent (and sample entropy) of EEG and GSR signals change together, which indicates the correlation among the brain and skin activities.

5. DISCUSSION AND CONCLUSION

For the first time, we evaluated the correlation between the reactions of the brain and skin in auditory stimulation, using the complexity theory. We quantified the changes in the complexity of EEG and GSR signals among various auditory stimulations by calculating their fractal dimension and sample entropy.

The results of the fractal analysis demonstrated that EEG signals experienced more significant changes by presenting relaxing, pop, and rock music, respectively. Similar results were obtained for the fractal exponent of GSR signals. The statistical analysis result showed that EEG and GSR signals experience more significant changes by moving from relaxing to pop and rock music. Besides, a strong correlation among the alterations of the complexity of EEG and GSR signals in response to different music was observed, which indicates a strong correlation among the brain and skin reactions to stimuli.

The result of the analysis of sample entropy of EEG and GSR signals was similar to the fractal analysis findings and indicated a strong correlation between the alterations of the complexity of EEG and GSR signals. Therefore, we conclude that the alterations of the activities of the brain and skin are coupled. The conducted investigation in this research is novel since, for the first time, we analyzed the correlation among the alterations of EEG and GSR signals in auditory stimulation.

We elaborate on the results by referring to the brain-skin connection. Due to the controlling role of the brain on the skin's activity through the nervous system,[31] the brain sends an impulse to the skin about the stimulus that we receive (music in this research). Therefore, depending on the type of music that we listen to, different messages are sent to the skin by the brain, which causes different reactions of the skin. In fact, the obtained results for the response of the skin to music are valid based on the obtained results in Ref. 32, which state the changes in the GSR signals due to listening to different music.

In future studies, we can expand this analysis to examine the correlation between brain and skin reactions to other types of stimuli (e.g. electrical stimuli). We can also investigate the correlation among other organs of humans. For instance, we can evaluate the correlation between facial muscles and brain reactions to different stimuli by analyzing EMG and EEG signals. Due to the interaction of different regions of the brain together,[33] we can also focus on analyzing the association of skin reaction with the changes in the complexity of EEG signals recorded from different areas of the brain. Besides, due to the interaction of various organs of the body within the network physiology,[34] the simultaneous analysis of their reactions to external stimuli can be examined. Working on the modeling of the relationship between external stimuli, EEG signals, and GSR signals is another future work that can potentially be done by employing fractional models[35] or computational analysis.[36,37] It should be noted that all these analyses also can be conducted for patients with different brain disorders to investigate how a damaged brain can control different organs within the physiological network. All these analyses have great importance in understanding human physiology.

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