OPEN ACCESS
Fractals, Vol. 29, No. 4 (2021) 2150175 (10 pages)

DOI: 10.1142/S0218348X21501759

World Scientific
www.worldscientific.com

EVALUATION OF THE COUPLING BETWEEN ELECTROENCEPHALOGRAM (EEG) AND GALVANIC SKIN RESPONSE (GSR) SIGNALS VERSUS THE COMPLEX STRUCTURE OF MUSIC

HAMIDREZA NAMAZI,[*,†,§] SHAFIUL OMAM,[†] KAMIL KUCA[*,‡] and ONDREJ KREJCAR[*,‡]

[*]*Center for Basic and Applied Research*
Faculty of Informatics and Management
University of Hradec Kralove, Hradec Kralove, Czechia

[†]*School of Engineering, Monash University*
Selangor, Malaysia

[‡]*Malaysia Japan International Institute of Technology (MJIIT)*
Universiti Teknologi Malaysia, Kuala Lumpur, Malaysia
[§]*hamidreza.namazi@monash.edu*

Received January 28, 2021
Accepted April 19, 2021
Published May 11, 2021

Abstract

Since skin activity, like other organs, is controlled by the brain, we decoded the correlation among the brain and skin responses in auditory stimulation by complexity-based analysis of EEG and GSR signals. Three pieces of music were selected according to the difference in the fractal exponent and sample entropy of embedded noises in them. We calculated the fractal dimension and sample entropy of EEG and GSR signals for 11 subjects in rest and response

[§]Corresponding author.

to these music pieces. The correlation coefficients of 0.9525 and 0.9822 in the case of fractal dimension and sample entropy demonstrated a strong correlation between the complexities of the GSR and EEG signals. Therefore, we can state that the skin and brain responses are coupled. This method can be applied to evaluate the relationship between the human brain and other organs.

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

1. INTRODUCTION

The brain is the center of the control system of our body. It regulates the body's actions and reactions. The brain does all its tasks by sending impulses through the nervous system. Skin is one of the critical parts of the human body that covers all around the body. Based on the controlling roles of the human brain, it also regulates the activates of human skin.

For years, some researchers have investigated human skin reactions, mainly for emotion recognition[1,2] and in response to stimulation.[3–5] Since physiological systems are highly complex under neural regulatory mechanisms,[6] an important area of work is quantifying the coupling between the alterations in different organs versus the alterations in brain activity. This paper focuses on the coupling between brain and skin activities. Since skin activity is controlled by the brain, a coupling should exist between their activities. According to the literature, some works analyzed the brain–skin connection. These studies can mainly be divided into two categories. In one category, scientists analyzed the alterations in the brain activity (mapped using different methods such as EEG,[7] MEG,[8] fMRI[9]) due to the changes in the condition of the skin (e.g. as the result of receiving somatosensory stimulation). In fact, these studies did not analyze skin activity in different conditions. In another category, researchers simultaneously evaluated the changes in skin conductance and brain reaction in various situations (mainly due to stimulation).[10–13] Besides several reported studies on these two categories, none of these studies brought the characteristics of external stimuli to their analyses by using the same feature to evaluate the alterations of brain and skin responses versus the alterations of the external stimuli. Based on our search, only our recently reported study in Ref. 14 found the correlation among the changes of GSR and EEG signals and olfactory stimuli using the complexity theory. According to the results, bigger changes in the complexity of olfactory stimuli led to bigger alterations in the complexity of GSR and EEG signals.

As it is known, EEG and GSR signals as the indicators of brain and skin activities are fractal.[14,15] On the other hand, audio signals have complex structures.[16] Therefore, the fractal theory can be used to investigate the correlation among the changes in the GSR and EEG signals' complexities versus the changes in the audio signals' complexity. Fractals are objects that show self-similarity or self-affinity.[17] Self-affine fractals are different than self-similar fractals, and we cannot see any relationship among their different parts. Many studies have investigated the complexity of various biological and physiological time series (EMG signals,[18] speech signals,[19] ECG signals,[20] DNA time series,[21] eye movements[22]) using fractal theory. Similarly, some studies have analyzed EEG signals using fractal theory. The works which investigated the influence of auditory[23] and electrical[24] stimuli, aging,[25] brain disorders,[26] and imaginary movements[27] on EEG signals' complexity can be mentioned. However, only our work in Ref. 14 and another study[28] has been reported in the literature that evaluated skin reaction using fractal analysis. In Ref. 28, the authors ran a fractal analysis on GSR signals to identify drivers' distraction in a driving experiment.

Other nonlinear analysis techniques also can be used to study the complexity of signals. Here, we chose sample entropy. We chose sample entropy since it is not dependent on the data's length and has relatively trouble-free implementation. In other words, we verify the result of the fractal analysis by analysis of sample entropy. Many works employed sample entropy to quantify the complexity of biological and physiological time series (EMG signals,[29] PCG signals,[30] ECG signals,[31] DNA time series,[32] eye movements[33]). We can also call some works on applying sample entropy in EEG signals analysis.[34,35] However, limited works employed sample entropy to analyze GSR signals.[36]

According to our search, no reported work has investigated the coupling among skin and brain activities and auditory stimuli by examining the complex structures of GSR, EEG, and audio signals. In this paper, we applied fractal analysis on the brain and skin signals to evaluate how the alterations of signals' complexities are correlated with the alterations in the complex structure of auditory stimuli. Besides, we verified the obtained results from the fractal analysis by computing and comparing the sample entropy of EEG and GSR signals and music.

In the following, we will detail the method of analysis. Then, we will describe data collection and analysis. We will describe the results of our analysis that are supported by statistical analysis. The discussion section will be provided as the last part of this paper.

2. METHOD

This study evaluated the coupling among the responses of the brain and skin in auditory stimulation. We benefited from fractal theory and sample entropy to evaluate the complexity of EEG and GSR signals. A greater level of complexity is quantified with a bigger value of fractal dimension and sample entropy.

We used the box-counting algorithm to compute the fractal exponent. This algorithm divides the object using same-size (ε) boxes, and then, it counts the number of boxes (N). It will repeat this process in further steps by changing the box size. Finally, it calculates the fractal dimension (FD)[37]:

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

Equation (2) shows the general form of fractal dimension:

$$\mathrm{FD}_c = \lim_{\varepsilon \to 0} \frac{1}{c-1} \frac{\log \sum_{j=1}^{N} r_j^c}{\log \varepsilon}. \tag{2}$$

In Eq. (2), c and r_j are the order, and the probability:

$$r_j = \lim_{\varepsilon \to 0} \frac{t_j}{T}. \tag{3}$$

In Eq. (3), T represents the total period of the signal.

If we consider a signal is in the form of $\{x(1), x(2), x(3), \ldots, x(n)\}$, a template vector of length k (embedding dimension) can be defined as $X_k(i) = \{x_i, x_{i+1}, x_{i+2}, \ldots, x_{i+k-1}\}$, and $d[X_k(i), X_k(j)]$ $(i \neq j)$ is the Chebyshev distance. Then, the sample entropy ($SamEn$) is formulated as[38]:

$$\mathrm{SamEn} = -\log \frac{A}{C}. \tag{4}$$

Considering ε as the tolerance ($0.2 \times$ standard deviation of data), A and C stand for the number of template vector pairs with conditions in (5) and (6):

$$d[X_{k+1}(i), X_{k+1}(j)] < \varepsilon, \tag{5}$$

$$d[X_k(i), X_k(j)] < \varepsilon. \tag{6}$$

We chose three pieces of music as auditory stimuli in this research. These pieces of music were taken from Ref. 39 in which, Hunt *et al.* embedded white noise, pink noise, and brown noise to the base music (Fur Elise by Beethoven) and analyzed the effect of alterations of the complexity of music on the alterations of the stride interval time series. In fact, we chose these pieces of music because of the difference in the fractal exponent and sample entropy of added noise to them that accordingly enabled us to evaluate the correlation between the complexities of EEG, GSR signals, and auditory stimuli. Table 1 lists the fractal exponents and sample entropies of embedded noises.

We played each music for the participants, and then we investigated the coupling between EEG and GSR signals by calculating the fractal exponent and sample entropy.

2.1. Data Collection and Analysis

Monash University has approved this study (# 18267). We ran the experiment on 11 participants (4 Male, 7 Female, 18–22 years old). After explaining the experiment to participants, asking several questions from them about their health conditions, and obtaining their consent, we initiated the experiment. Participants did not drink alcoholic/caffeine beverages within 48 h before the experiment.

We performed the experiments in a quiet room without external disturbances. Figure 1 shows the

Table 1 The Complexity of Different Noises Embedded in the Base Music.

Type of Noise	Fractal Dimension	Sample Entropy
White noise	1.5	2.2
Pink noise	1	1.75
Brown noise	0.5	0.25

Fig. 1 The setup of the experiment.

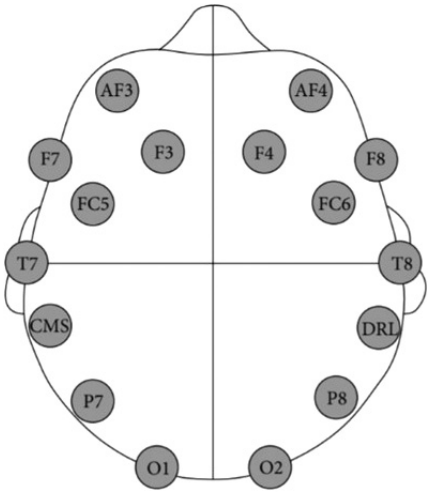

Fig. 2 Placement of EEG electrodes.

experiment set up by attaching EMOTIV EPOC EEG (14 recording and 2 reference electrodes) and Shimmer GSR devices to the subject. The placement of EEG electrodes was based on the 10–20 system (see Fig. 2). Also, in the case of GSR recording, two electrodes were connected to the fingers of the right hand of each participant. Participants washed and dried their fingers before the experiment, and we did not add any gel on their skin and scalp since it was not required for the used EEG and GSR devices. During the experiment, participants sat on a chair in a comfortable position. The recording of EEG and GSR data was performed at 128 Hz and 51.2 Hz, respectively. The computer's speaker was used for playing the music files for subjects.

In the first step, we collected EEG and GSR signals during rest for one minute. Then, we presented white, pink, and brown noise-based music to the participants and collected their EEG and GSR signals. Each music was played for one minute, and one minute rest was considered between every two stimulations. The experiment was repeated in a second session. Due to the poor connection (or disconnection) of the EEG device in two periods of data collection, we excluded the recorded data in those sessions.

We wrote a code that firstly removed the DC offset (at approximately 4200 μV) from raw EEG signals. After that, we denoised EEG and GSR signals using Butterworth filters at 1–40 Hz for EEG signals and the 20 Hz cut-off frequency for GSR signals. We checked the filtered versus raw signals to ensure the quality of the designed filter.

We calculated the fractal exponent and sample entropy of filtered signals. The box-counting algorithm was run using boxes with the sizes of $\frac{1}{2}, \frac{1}{4}, \frac{1}{8}, \frac{1}{16}, \ldots$. All the pre-processing and processing steps for the analysis of signals were conducted in MATLAB.

We performed multiple comparisons between the complexity of EEG signals (and also GSR signals) by running the posthoc Tukey test. We also calculated Cohen's d to quantify the effect size. The coupling among the alterations in the complexities of EEG signals, GSR signals, and auditory stimuli was examined using the Pearson correlation coefficient. The significance level of 0.05 was chosen for our analysis.

3. RESULTS

The results in this section are based on the average of analyzed data from all channels in both sessions of the experiment. The alterations in the EEG signals' fractal exponent are illustrated in Fig. 3a. We also illustrated the fractal exponents of added noises to the base music in Fig. 3b.

As Fig. 3a shows, we can see that the EEG signals' fractal exponent increased in response to different music. By comparing with Fig. 3b, we can see that the decrement in the fractal exponent of

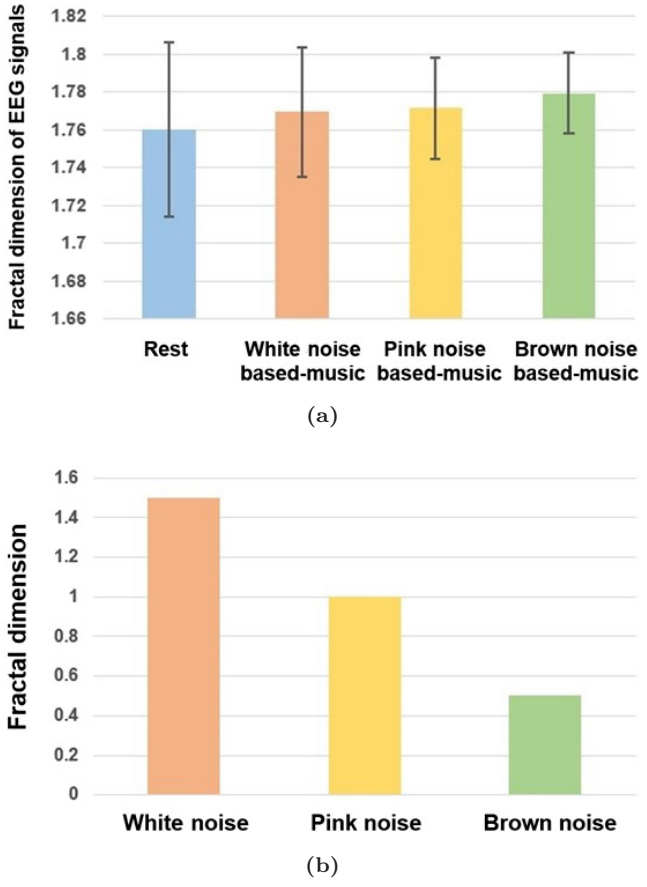

Fig. 3 The fractal exponent of EEG signals **(a)** and added noise to music **(b)**.

Table 2 Comparisons of EEG Signals' Fractal Exponents.

Pairwise Comparison	*p*-Value	Cohen's *d*
Rest versus white noise-based music	0.8016	−0.2270
Rest versus pink noise-based music	0.6842	−0.3009
Rest versus brown noise-based music	0.2508	−0.5361
White noise- versus Pink noise-based music	0.9969	−0.0674
White noise- versus Brown noise-based music	0.7605	−0.3479
Pink noise- versus Brown noise-based music	0.8647	−0.3272

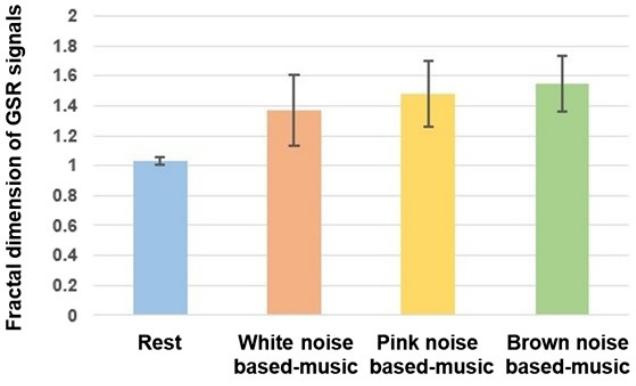

Fig. 4 The fractal exponent of GSR signals.

auditory stimuli led to the increment in the fractal exponent of EEG signals. In other words, making a larger alteration in the complexity of auditory stimuli led to a larger alteration in the EEG signals' complexity. The correlation coefficient of $r = -0.9476$ proves a strong correlation among the complexities of EEG signals and music.

Comparisons of the fractal exponents among various conditions (Table 2) indicate that bigger alterations in the music's complexity led to bigger changes in EEG signals' complexity. In this research, we look for the coupling among the changes of EEG and GSR signals, not the significance of their changes between various conditions. Besides, qualitatively comparing of effect sizes in this table indicates that brown noise-based music had the biggest influence on the EEG signals' fractal exponents. The fractal exponents of GSR signals are shown in Fig. 4.

Based on this figure, the fractal exponent of GSR signals increased in response to stimulation using different music. In fact, the application of white noise- to brown noise-based music caused the increment in the GSR signals' complexity. By comparing with Fig. 3b, we can see that the decrement in the fractal exponent of auditory stimuli led to the increment in the fractal exponent of GSR signals. In other words, making larger alterations in the complexity of auditory led to larger alterations in the GSR signals' complexity. The correlation coefficient of $r = -0.9928$ proves the strong correlation among the complexities of GSR signals and music.

Comparisons of the GSR signals' fractal exponents among various conditions (Table 3) indicate more significant alterations in the complexity of GSR signals by making greater alterations in the music's complexity. Besides, comparing the effect sizes indicates that brown noise-based music had the biggest influence on the GSR signals' fractal exponent.

Comparing the effect sizes between Tables 2 and 3 in the case of different auditory stimulations versus rest suggests that auditory stimuli had more significant influences on altering the complexity of

Table 3 Comparison of Fractal Exponents of GSR Signals.

Pairwise Comparison	p-Value	Cohen's d
Rest versus white noise-based music	0.1520	−2.0112
Rest versus pink noise-based music	0.0009	−2.8553
Rest versus brown noise-based music	0.0003	−3.8633
White noise- versus Pink noise-based music	0.2739	−0.4780
White noise- versus Brown noise-based music	0.1492	−0.8462
Pink noise- versus Brown noise-based music	0.9880	−0.3498

GSR signals than EEG signals. In other words, the skin shows a greater change in its activity than the brain.

Comparing Fig. 3a with Fig. 4 and considering the correlation coefficient of $r = 0.9525$ indicates a strong coupling among the fractal structures of EEG and GSR signals in the case of different music when a more significant alteration in the fractal exponent of auditory stimuli led to a more significant alteration in the fractal exponents of EEG and GSR signals.

The sample entropy of EEG signals in different conditions is shown in Fig. 5a. For comparison, we showed the sample entropy of added noises to the base music in Fig. 5b.

As Fig. 5a illustrates, the entropy of EEG signals increased in response to different music. In fact, the decrement in the sample entropy of auditory stimuli (Fig. 5b) is reflected in the increment of the sample entropy of EEG signals. In other words, bigger alterations in the music's complexity led to bigger changes in the EEG signals' complexity. This strong correlation among the complexities of music and EEG signals can be concluded from the correlation coefficient ($r = -0.8477$).

Comparisons of the entropies among various conditions (Table 4) demonstrate that making bigger changes in the sample entropy of music caused more significant alterations in the EEG signals' entropy. As previously indicated, the significance of changes of the EEG and GSR signals' complexities are not considered in this research. Furthermore, qualitatively comparing of effect sizes indicates that brown noise-based music had the biggest impact on the EEG signals' fractal exponent.

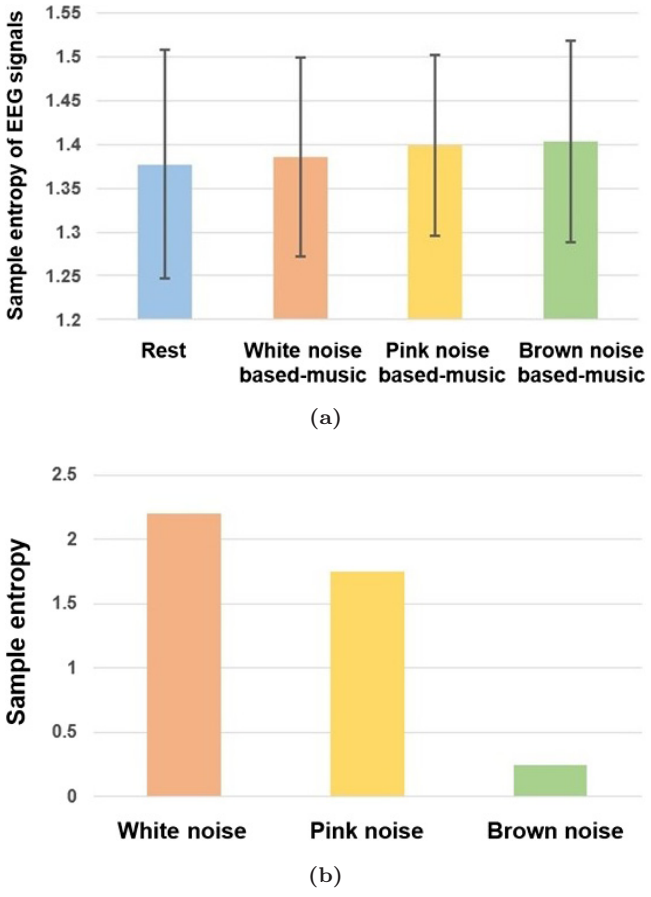

Fig. 5 The sample entropy of EEG signals **(a)** and added noise to music **(b)**.

Table 4 Comparison of Sample Entropy of EEG Signals.

Pairwise Comparison	p-Value	Cohen's d
Rest versus white noise-based music	0.9954	−0.0681
Rest versus pink noise-based music	0.9334	−0.1786
Rest versus brown noise-based music	0.8887	−0.2091
White noise- versus Pink noise-based music	0.9835	−0.1170
White noise- versus Brown noise-based music	0.9604	−0.1524
Pink noise- versus Brown noise-based music	0.9991	−0.0432

By comparing Fig. 5a with Fig. 3a and the presented results between Tables 4 and 2, we can indicate that the results of the analysis of sample entropy verify the obtained results from the fractal analysis of EEG signals. The changes in the sample entropy of GSR signals are shown in Fig. 6.

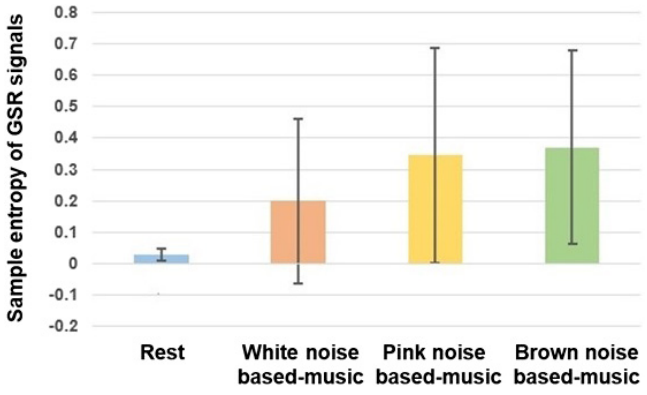

Fig. 6 The sample entropy of GSR signals.

The sample entropy of GSR signals increased due to stimulations using different music (white noise- to the brown noise-based music). Therefore, by comparing with Fig. 5b, we can see that the decrement in the sample entropy of auditory stimuli led to the increment in the sample entropy of GSR signals. In other words, making a bigger alteration in the music's complexity led to a bigger alteration in the complexity of GSR signals. The correlation coefficient of $r = -0.7753$ proves the strong correlation among the complexity of GSR signals and music.

By referring to comparisons of the entropy of GSR signals among various conditions (Table 5), we can see more significant alterations in the GSR signals' complexity by making greater alterations in the music's complexity. Besides, comparing the effect sizes indicates that brown noise-based music had the most significant influence on the entropy of the GSR signals.

By comparing Fig. 6 with Fig. 4 and the presented results between Tables 3 and 5, we can indicate that the analysis results of entropy verify the fractal analysis results. Besides, comparing Fig. 5a with Fig. 6 and the correlation coefficient of $r = 0.9822$ demonstrates a strong coupling among the entropies of EEG and GSR signals in the case of various music, when a bigger change in the entropy of auditory stimuli led to a bigger alteration in the entropy of EEG and GSR signals.

Therefore, based on the conducted analysis, the changes in the complexities of GSR and EEG signals are coupled, which reflects the correlation between the brain and skin activities.

Table 5 Comparison of Sample Entropy of GSR Signals.

Pairwise Comparison	p-Value	Cohen's d
Rest versus white noise-based music	0.1520	−0.9168
Rest versus pink noise-based music	0.0009	−1.3001
Rest versus brown noise-based music	0.0003	−1.5636
White noise- versus Pink noise-based music	0.2739	−0.4757
White noise- versus Brown noise-based music	0.1492	−0.5981
Pink noise- versus Brown noise-based music	0.9880	−0.0797

4. DISCUSSION AND CONCLUSION

We quantified the correlation among the brain and skin responses to auditory stimulations using the complexity theory. Since we also wanted to incorporate the complexity of auditory stimuli, we used three music pieces that contained embedded white, pink, and brown noise with different complexities. We ran the fractal analysis on the EEG and GSR signals at rest and listening to the music.

The results demonstrated that EEG signals' fractal exponent experiences more significant changes by making bigger alterations in the complexity of embedded noise in the base music. Similarly, GSR signals' fractal exponent experiences more significant alterations in this trend. The statistical analysis also indicated a strong correlation between the changes of EEG and GSR signals' complexities in rest and auditory stimulation. Therefore, the complexities of EEG and GSR signals change more significantly as the changes in the complexity of embedded noises in the music become more significant. In other words, a music piece that causes greater alteration in the complexity of brain reaction accordingly causes a larger alteration in the complexity of skin reaction.

Besides, we also analyzed the sample entropy of EEG and GSR signals. The analysis of sample entropy demonstrated similar findings with the fractal analysis findings and indicated a strong coupling between the EEG and GSR signals' complexities. Therefore, we conclude that the changes in the brain and skin responses and applied auditory stimuli are coupled. In fact, for the first time, we evaluated the correlation between the alterations of EEG and GSR signals and auditory stimuli.

We elaborate on the obtained results by referring to the skin-brain connection. Since the brain

controls the skin's activity,[40] when we listen to an auditory stimulus, an impulse is sent to the brain, and accordingly, the brain sends a message to the skin about the stimulus. In Ref. 41, it was shown that the alterations of the complexity noise affect the changes in EEG signals' complexity. Therefore, because of brain–skin connection, the trend of alterations of the complexity of EEG signals and music is reflected in the trend of changes in the complexity of GSR signals and music. In fact, the results for the response of the skin to music are valid according to the results in Ref. 42, which indicate the alterations in the GSR signals due to listening to various pieces of music.

It should be mentioned that evaluating the coupling among brain–skin activities is not limited to auditory stimulation. We can expand this analysis in the case of other external stimuli (e.g. somatosensory stimuli) to evaluate how the brain and skin's responses are related. Besides, we can expand our investigation to assess the coupling among other organs of humans. For example, we can decode the coupling between human facial muscles and the brain by analyzing EMG and EEG signals. Since different organs also dynamically interact,[43] we can work on generating a network physiology map by simultaneous analysis of complex structures of various physiological signals (e.g. GSR, EMG, EEG, ECG signals).

It should be noted that our method of analysis can be used to see how the activities of skin (or other human organs such as heart and muscle) and brain are coupled for patients with some brain or other organs' disorders. Another branch of work is the mathematical modeling of the relation between skin (or other organs) activity, brain activity, and the characteristics of external stimuli using mathematical equations (e.g. fractional diffusion equations[44]). This modeling will potentially able us to forecast the brain and skin responses based on the applied stimuli. All these investigations help researchers to solve many questions about the coupling between the brain and other organs that has great importance in physiology.

ACKNOWLEDGMENT

We would like to acknowledge the assistance of Sue Sim and Visvamba Nathan in data collection and analysis. This work was also supported in part by the project (2021/2205), Grant Agency of Excellence, University of Hradec Kralove, Faculty of Informatics and Management, Czech Republic.

REFERENCES

1. A. Raheel, M. Majid, M. Alnowami and S. M. Anwar, Physiological sensors based emotion recognition while experiencing tactile enhanced multimedia, *Sensors* **20**(14) (2020) 4037.
2. T. Paul *et al.*, Human emotion recognition using GSR and EEG, *Int. J. Sci. Res. Publ.* **10**(5) (2020) 394–400.
3. D. R. Bach *et al.*, Time-series analysis for rapid event-related skin conductance responses, *J. Neurosci. Methods* **184**(2) (2009) 224–234.
4. E. Gatti *et al.*, Emotional ratings and skin conductance response to visual, auditory and haptic stimuli, *Sci. Data* **5** (2018) 180120.
5. S. Akdemir *et al.*, Investigation into the effects of Classical Turkish Music on galvanic skin response and skin temperature of schizophrenic patients, *J. Networking Technol.* **1**(4) (2010) 181–188.
6. A. Bashan *et al.*, Network physiology reveals relations between network topology and physiological function, *Nat. Commun.* **3** (2012) 702.
7. H. Hogendoorn, M. Kammers, P. Haggard and F. Verstraten, Self-touch modulates the somatosensory evoked P100, *Exp. Brain Res.* **233**(10) (2015) 2845–2858.
8. H. Mochizuki *et al.*, Itching-related somatosensory evoked potentials, *Pain* **138**(3) (2008) 598–603.
9. B. Querleux *et al.*, Neural basis of sensitive skin: An fMRI study, *Skin Res. Technol.* **14**(4) (2008) 454–461.
10. C. A. Torres-Valencia, H. F. García-Arias, M. A. A. López and A. A. Orozco-Gutiérrez, Comparative analysis of physiological signals and electroencephalogram (EEG) for multimodal emotion recognition using generative models, in *2014 XIX Symposium on Image, Signal Processing and Artificial Vision*, Armenia, 2014, pp. 1–5, doi:10.1109/STSIVA. 2014.7010181.
11. H. D. Critchley, R. Elliott, C. J. Mathias and R. J. Dolan, Neural activity relating to generation and representation of galvanic skin conductance responses: A functional magnetic resonance imaging study. *J. Neurosci.* **20**(8) (2000) 3033–3040.
12. L. M. Williams *et al.*, Arousal dissociates amygdala and hippocampal fear responses: evidence from simultaneous fMRI and skin conductance recording, *NeuroImage* **14** (2001) 1070–1079.
13. M. Gamer, T. Bauermann, P. Stoeter and G. Vossel, Covariations among fMRI, skin conductance, and behavioral data during processing of concealed information, *Hum. Brain Mapp.* **28**(12) (2007) 1287–1301.

14. S. Omam *et al.*, Complexity-based decoding of brain-skin relation in response to olfactory stimuli, *Comput. Methods Programs Biomed.* **184** (2020) 105293.
15. M. Soundirarajan *et al.*, Analysis of brain-facial muscle connection in the static fractal visual stimulation, *Int. J. Imaging Syst. Technol.* (2020) 1–7. doi:10.1002/ima.22480.
16. M. R. A. Ahamed, M. H. Babini and H. Namazi, Complexity-based decoding of the relation between human voice and brain activity, *Technol. Health Care* **28**(6) (2020) 665–674.
17. C. L. Kiew *et al.*, Fractal-based analysis of the relation between the fractal structures of machined surface and tool wear in turning operation, *Fractals* **27**(6) (2019) 1950094.
18. M. H. Babini, V. V. Kulish and H. Namazi, Physiological state and learning ability of students in normal and virtual reality conditions: Complexity-based analysis, *J. Med. Internet Res.* **22**(6) (2020) e17945.
19. M. R. A. Ahamed, M. H. Babini and H. Namazi, Complexity-based analysis of brains' synchronization in human-human interaction, *Fractals* **28**(7) (2020) 2050102.
20. S. M. Kamal, M. H. Babini, O. Krejcar and H. Namazi, Complexity-based decoding of the coupling among heart rate variability (HRV) and walking path, *Front. Physiol.* **11** (2021) 602027.
21. H. Namazi and N. Mat Dawi, Information and complexity-based analysis of the variations of the coronavirus genome between different countries, *Fractals* **28**(7) (2020) 2050134.
22. H. Alipour, H. Namazi, H. Azarnoush and S. Jafari, Fractal-based analysis of the influence of color tonality on human eye movements, *Fractals* **27**(3) (2019) 1950040.
23. A. K. Maity *et al.*, Multifractal detrended fluctuation analysis of alpha and theta EEG rhythms with musical stimuli, *Chaos Solitons Fractals* **81**(A) (2015) 52–67.
24. K. Tripanpitak, W. Viriyavit, S. Y. Huang and W. Yu, Classification of pain event related potential for evaluation of pain perception induced by electrical stimulation, *Sensors* **20**(5) (2020) 1491.
25. A. P. Anokhin *et al.*, Age increases brain complexity, *Electroencephalogr. Clin. Neurophysiol.* **99** (1996) 63–68.
26. G. V. Portnova, Lack of a sense of threat and higher emotional lability in patients with chronic microvascular ischemia as measured by nonlinear EEG parameters, *Front. Neurol.* **11** (2020) 122.
27. V. V. Grubov, A. A. Badarin, N. Frolov and E. Pitsik, Analysis of real and imaginary motor activity with combined EEG and fNIRS, *Saratov Fall Meeting 2019: Computations and Data Analysis: from Nanoscale Tools to Brain Functions* (2020), doi:10.1117/12.2564387.
28. O. Dehzangi, V. Rajendra and M. Taherisadr, Wearable driver distraction identification on-the-road via continuous decomposition of galvanic skin responses, *Sensors* (*Basel*) **18**(2) (2018) 503.
29. M. Soundirarajan, M. Augustynek, O. Krejcar and H. Namazi, Evaluation of the correlation between facial muscle and brain activities in auditory stimulation, *Fractals* **29**(1) (2021) 2150100.
30. H. Namazi and O. Krejcar, Analysis of pregnancy development by complexity and information-based analysis of fetal phonocardiogram (PCG) signals, *Fluct. Noise Lett.* (2020), doi:10.1142/S0219477521500280.
31. H. Namazi, D. Baleanu and O. Krejcar, Age-based analysis of heart rate variability (HRV) for patients with congestive heart failure, *Fractals* **29**(3) (2021) 2150135.
32. H. Namazi, E. Herrera-Viedma and O. Krejcar, Complexity-based detection of similarity between animal coronaviruses and SARS-CoV-2 in humans, *Fractals* **28**(7) (2020) 2150031.
33. K. Harezlak and P. Kasprowski, Searching for chaos evidence in eye movement signals, *Entropy* **20** (2018) 32.
34. T. Angsuwatanakul, J. O'Reilly, K. Ounjai, B. Kaewkamnerdpong and K. Iramina, Multiscale Entropy as a new feature for EEG and fNIRS analysis, *Entropy* **22** (2020) 1–23.
35. J. Prasanna *et al.*, Detection of focal and non-focal electroencephalogram signals using fast Walsh-Hadamard transform and artificial neural network, *Sensors* (*Basel*) **20**(17) (2000) 4952.
36. S. H. Wang, H. T. Li, E. J. Chang and A. Y. Wu, Entropy-assisted emotion recognition of valence and arousal using XGBoost classifier, in *Artificial Intelligence Applications and Innovations* (2018), doi:10.1007/978-3-319-92007-8_22.
37. A. Ahamed *et al.*, Complexity based analysis of the influence of machining parameters on the surface finish of drilled holes in drilling operation, *Fractals* **27**(6) (2019) 1950087.
38. H. Namazi, Complexity-based classification of the coronavirus genome versus genomes of the human immunodeficiency virus (HIV) and dengue virus, *Fractals* **28**(7) (2020) 2050129.
39. N. Hunt *et al.*, The influence of auditory-motor coupling on fractal dynamics in human gait, *Sci. Rep.* (2014), doi:10.1038/srep05879.
40. H. S. Kim and G. Yosipovitch, The skin microbiota and itch: Is there a link? *J. Clin. Med.* **9**(4) (2020) 1190.
41. L. Lundqvist, F. Carlsson, P. Hilmersson and P. Juslin, Emotional responses to music: Experience,

expression, and physiology, *Psychol. Music* **37**(1) (2008) 61–90.
42. Y. Qin, 3D music impact on autonomic nervous system response and its therapeutic potential, in *2020 IEEE Conference on Multimedia Information Processing and Retrieval (MIPR)*, Shenzhen, Guangdong, China (2020), pp. 364–369, doi:10.1109/MIPR49039.2020.00080.
43. R. P. Bartsch, K. K. L. Liu, A. Bashan and P. C. Ivanov, Network physiology: How organ systems dynamically interact, *PLoS One* **10**(11) (2015) e0142143.
44. H. Namazi and V. V. Kulish, Fractional diffusion based modelling and prediction of human brain response to external stimuli, *Comput. Math. Methods* (2020) 1–11, doi:10.1155/2015/148534.