Non-linear Analysis of Psychophysiological Effects of Auditory Stimuli using Fractal Mining

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Abstract— *While spectral analysis (e.g., Fast Fourier Transformation) of electroencephalogram (EEG) has been one of the most well established parameters in psychophysiology, physiological implication of fractal analysis has not been established. Further, systematic examination of the association between the waveforms of auditory stimuli and EEG is an untouched area of research. In the present study, we used fractal analysis and data mining techniques, and created a method for finding the association between fractal dimensions of auditory stimuli and fractal dimensions of EEG. Applying our method, we found strong associations between signal complexity in auditory input and the resulting EEG data, with confidence values exceeding 90% in several of the associations. Our success in this initial application could potentially be generalized to further brain activity analysis.*

Keywords: Fractal Dimensions, Association Mining, Electroencephalogram

1. Introduction

Music is believed to have differential psychophysiological effects on humans. The notion on the effects of music dates back to the ancient era when Pythagoras created several diatonic scales and discussed their psychophysiological effects. Studies have shown that music can affect and stimulate different parts of the brain and can help with stress reduction, depression alleviation, and information recall. Such effects of music can be quantitatively studied using Electroencephalogram (EEG) [1], [2], [3], [4]. EEG refers to the electrical activity of the brain neurons captured from scalp surface. Each EEG electrode reflects electrical activity of about 100 neurons underneath the electrode and it produces tracing of pulses at various frequencies.

Even though studying the brain activity using linear analysis of electroencephalogram (EEG) is one of the most widely accepted research techniques in psychology and neuroscience, nonlinear analysis of EEG has not been extensively explored. Also, to the best of our knowledge, a systematic examination of the mathematical relationship between auditory stimuli and EEG has not been reported. The purpose of this work was to examine the psychophysiological effects of various auditory input in the form of synthetic music using fractal analysis and data mining techniques. In particular, we discovered the association between the auditory stimuli and the resulting EEG using fractal dimensions. Psychologists believe that there is a particular fractal dimensionality in nature and when the incoming stimuli imitates this fractal dimension, the nervous system would resonate with this fractal dimension and show a particular pattern.

The auditory stimuli and EEG are both high-dimensional time-series datasets that contain a very large number of features, some of which are highly correlated. This high-dimensionality of the data can make the data analysis task extremely difficult and time-consuming. A “fractal” [5] is defined to be a self-similar set of data points that consists of pieces similar to the original set, e.g., Sierpinski’s Triangle. The “fractal dimension” is an estimate of the degrees of freedom of a data set [6]. The fractal dimension estimates the intrinsic dimension of the data and is a good indicator of the spread of the data. It is a useful tool to characterize the non-linearity and complexity of a given dataset. The fractal dimension of a dataset can make the data mining task more efficient and effective. The fundamental principle of fractal analysis is to identify the number of data points that self-correlate across scales, each of which is considered as a “dimension”. Fractal dimension has been utilized as an effective tool for modeling various real world time series data with high complexity and irregularity [7], [8].

Our objective was to develop a working method for providing meaningful analysis of psychophysiological experiments. We analyzed EEG data collected from subjects who were exposed to auditory input, as well as the auditory data itself. We used fractal dimension analysis [9] and association mining [10] to provide the psychology researchers with information about their tests that they couldn’t have otherwise discovered. To the best of our knowledge, this approach hasn’t been implemented prior to this work.

The remainder of the paper is organized as follows. In section 2, we present the background pertaining to this work. In section 3, we present our analysis methods, describe our datasets, and present the experimental results. Finally, in section 4, we will provide concluding remarks and scope of future research.

2. Background

2.1 Fractal Dimension

The fractal dimension of a dataset is the degree of self-similarity that exists within the data. A fractal dimension is a non-negative real value that quantifies the complexity and irregularity of a dataset. Several methods have been developed for computing the fractal dimension of data.

Box-counting dimension [6] is by far the most commonly used fractal dimension. If $N(\epsilon)$ is the minimum number of n-dimensional boxes with sides of ϵ needed to cover the fractal, then the box-counting dimension is expressed as:

$$d_b = -\lim_{\epsilon \to 0} \frac{\ln N(\epsilon)}{\ln(\epsilon)}$$

Correlation dimension [11] is widely used when the data is available as a set of isolated points and is particularly suitable for time series data. It is easy to calculate, but its effectiveness is reduced with the presence of noise in data. If $C(\epsilon)$ is the fraction of pairs of points within a distance of ϵ, then the correlation dimension is defined as:

$$d_c = \lim_{\epsilon \to 0} \frac{C(\epsilon)}{\ln(\epsilon)}$$

Regularization dimension [9] is computed by smoothing (or regularizing) data by convoluting it with a Gaussian kernel. The regularization dimension quantifies how the length of a smoothed signal converges to infinity as Gaussian kernel width approaches 0. It is very effective in dealing with noisy data. If δ is the Gaussian kernel width and l_δ is the length of the smoothed signal, then the regularization dimension is formally expressed as:

$$d_r = 1 - \lim_{\delta \to 0} \frac{\ln l_\delta}{\ln \delta}$$

2.2 Association Mining

The goal of association mining is to derive correlations among multiple features of a dataset [10]. An association rule is an implication of the form $X \Rightarrow Y_{[Supp,Conf]}$, where X and Y are disjoint itemsets, $Supp$ is the *support* of $X \cup Y$ indicating the percentage of total records that contain both X and Y, and $Conf$ is the *confidence* of the rule that is defined as $Supp(X \cup Y)/Supp(X)$. The intuitive meaning of such a rule is that records of the dataset that contain X tend to contain Y.

A typical example of an association rule obtained from music experiment is $2.55 \geq FD(Music) > 2.45 \Rightarrow FD(EEG_{T6}) > 1.86_{[0.12,0.94]}$. This implies 94% of the time when the fractal dimension of music is between 2.45 and 2.55, the fractal dimension of the EEG response at the right temporal lobe T6 will be more than 1.86, this constitutes 12% of the data records. Here the confidence of the rule is 94% and the support of the rule is 12% .

The goal in a particular application is to find all association rules that satisfy user-specified minimum support and minimum confidence constraints. Association rules are generated in two steps. The itemsets having minimum support (called *large itemsets*) are discovered first and then these large itemsets are used to generate the association rules with minimum confidence. The *Apriori* association mining algorithm [10] has widely been accepted as the algorithm of choice in many applications. The process of generating large itemsets in Apriori consists of several passes and the large itemsets found in one pass are used to generate large itemsets for the next pass. In the k^{th} pass, the candidate itemsets of length k (C_k) are generated by joining large itemsets of length $k-1$ (L_{k-1}) and leaving out itemsets containing any non-large subset. Formally, $L_{k-1} * L_{k-1} = \{X \cup Y | X, Y \in L_{k-1}, |X \cap Y| = k-2\}$. All candidate k-itemsets having support values greater than the minimum support threshold constitute the large k-itemsets L_k. Formally, $L_k = \{X | X \in C_k, Supp(X) \geq Supp_{min}\}$. After all the large itemsets are generated, for every large itemset L, the following set of rules are generated: $\{A \Rightarrow (L - A) \mid A \subset L, A \neq \emptyset, Supp(L)/Supp(A) \geq Conf_{min}\}$.

2.3 Previous Work

Fractal dimensions have been used widely to analyze music. Gunasekaran and Revathy [12] used fractal dimensions of music segments to identify musical instruments using neural network classifiers. Das and Das [13] showed how the fractal dimensions calculated from the same song varies when it is performed by different singers. Bigerelle and Iost [7] used fractal dimensions to classify different types of music and demonstrated that fractal dimensions can distinguish different aspects of music effectively.

Fractal analysis of EEG signals have been found to be effective in neuroscience. Preissl et al. [14] showed how fractal dimension can be used to characterize the complexity of short-duration EEG signals. Jacquin et al. [15] combined wavelet and fractal analysis of EEG signals to detect seizures. Chouvarda et al. [16] used the fractal dimensions of EEG signals to study the different sleep stages in individuals. Easwaramoorthy and Uthayakumar [8] proposed a method for discriminating healthy and the epileptic individuals using a multi fractal analysis of EEG signals.

The influence of music on EEG has also been investigated for studying brain activities. Yuan et al. [1] studied the effect of music on EEG power spectrum. They showed that the presence of music makes significant changes in certain EEG power spectrum that are closely related to the emotional state of the nervous system. Bhattacharya et al. [17] analyzed the interdependency between different brain regions based on asymmetric similarity of EEG signals in response to music. Jausovec et al. [2] investigated the influence of music on brain activity during learning and showed that classical music can result in better task performance and less complex EEG patterns. Srinivasan et al. [3] investigated the effect of music on mental fatigue by performing statistical analysis (ANOVA) on EEG signals and showed that the presence of music reduces mental fatigue during physical activities like jogging. Lin et al. [4] used machine-learning algorithms identify different emotional states based on EEG responses to music. Ito et al. [18] studied the association between an individual's egogram score based personality and the EEG pattern in response to music.

3. Methods and Experiments

3.1 Overview

As described in the previous section, fractal analysis has been used for analyzing music and EEG signals. The influence of music on brain activities has also been studied via EEG analysis. But, to the best of our knowledge, no computational framework has been presented to investigate the association between the fractal dimensions of music stimuli and the fractal dimensions of EEG responses. Fig. 1 shows the workflow of our method for finding the associations between auditory stimuli and the resulting multichannel EEG signals using fractal dimensions. The first step was to pre-process the auditory stimuli and EEG data. In our experiments, the auditory stimuli consisted of different pieces of synthetic music, varying in scale and note. The next step was to compute fractal dimensions from the auditory stimuli and the resulting EEG signals. The final step was to discover the associations between the fractal dimensions of the auditory stimuli and the fractal dimensions of the multi-channel EEG signals.

We believe that the fractal dimension computed from a music segment is a good measure of its pitch variation and thus will be helpful in a meaningful analysis of the psychophysiological effects of music. We used the "regularization dimension" approach [9] for fractal dimension calculation since it is more effective in dealing with noisy data. Because of the adaptive nature of signal smoothing, the regularization dimension is robust and allows for small step variation in the Gaussian kernel [19].

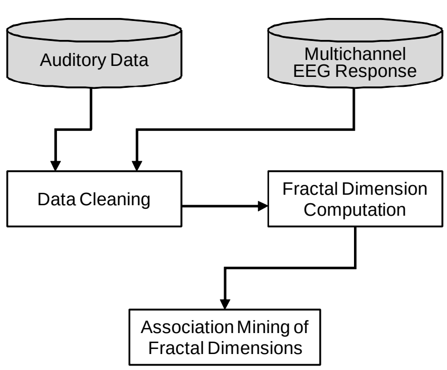


Fig. 1: The workflow for analyzing the EEG responses to auditory stimuli.

3.2 Data Collection

Our data collection involved ten healthy adult female subjects who were exposed to eight 2-minute long synthetic music pieces with varying degrees of fractal dimensions in random order. In order to keep all the parameters constant except for the fractal dimensions, a software package called FractMus[1] was used to generate the music pieces with different degrees of randomness, although all were composed in natural minor mode (one of the common modes local population is used to hearing in Irish folk songs) with three different pitches of electronic piano sound in 8 beats, 16 beats, and 32 beats, respectively. Throughout the music-listening task, eight-channels of EEGs based on the International 10-20 Method were measured using Biopac system at frontal lobe (F3, F4, F7, & F8) and at temporal lobe (T3, T4, T5, & T6). The channels F3, F4, F7, and F8 were selected in order to identify the emotional balance and function and the channels T3, T4, T5, and T6 were selected in order to identify the brain activity associated with sound processing function, respectively.

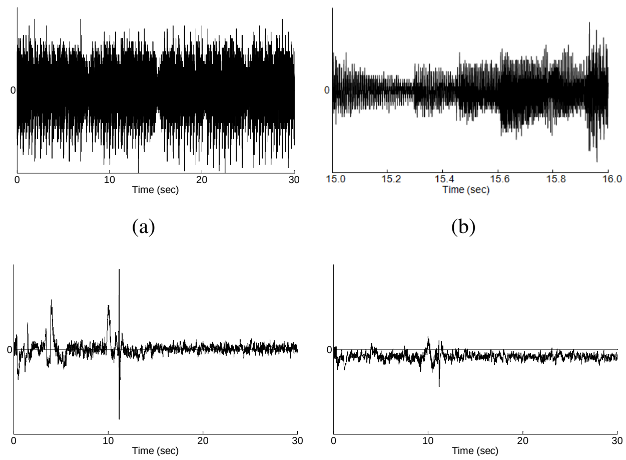
3.3 Data Analysis

The music files were generated in Waveform Audio File Format (WAV) and EEG data were generated in ASCII format. The WAV format was used because of its high quality, but the WAV files contain many features that are not relevant to the fractal analysis task. Both the music and EEG datasets were converted into a set of vectors using MATLAB. Each music piece was divided into four segments (30 seconds each). This created a total of thirty two 30-second long audio segments. For each audio segment, eight EEG channels were recorded; resulting in 256 EEG signals for each subject.

Fig. 2(a) shows the waveform of a 30-second music segment and Fig. 2(b) shows the waveform of this segment zoomed into the one second interval between 15 and 16 seconds. Figs. 2(c) and 2(d) show the EEG signals measured for a randomly selected subject at channels F3 (left frontal lobe) and T6 (right temporal lobe) in response to this music segment. The graphs clearly show the fractal aspects of these complex time series data. It is also evident that different EEG patterns are produced at different channels.

Our goal was to generalize any association that may exist between the music stimuli and the resulting EEG. Each audio and EEG signal was analyzed using the FracLab toolbox of MATLAB. The *regularization dimension* was computed for each 30-second music segment and for the corresponding EEG signals from eight channels. Fig. 3 shows the fractal dimensions computed from all eight music pieces with each music piece split into 30-second segments. It can be seen that different fractal patterns exist in the music pieces.

[1] http://www.gustavodiazjerez.com/fractmus_overview.html



(a) (b)

(c) (d)

Fig. 2: The waveform of a 30-second music segment and the resulting EEG signals measured for a randomly selected subject - (a) The 30-second music segment, (b) Zoomed into one second, (c) EEG at F3, and (d) EEG at T6.

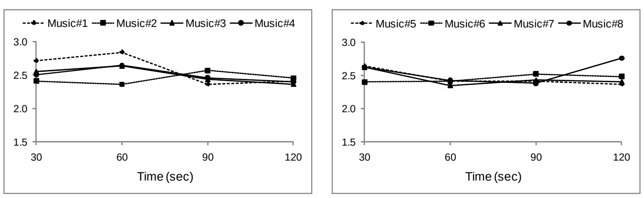
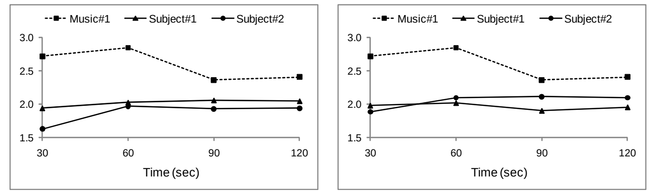


Fig. 3: The fractal dimensions of eight music pieces with each music piece split into 30-second segments.

Fig. 4 shows the fractal dimensions of EEG signals measured for two randomly selected subjects in response to music#1. Fig. 4(a) shows the EEG fractal dimensions for channel F3 and Fig. 4(b) shows the EEG fractal dimensions for channel T6. It can be seen that different subjects respond to the same music stimuli in different ways and the same individual exhibit different patterns at different channels. Therefore, it is not possible to discover any relationship between music stimuli and EEG responses using linear regression methods. That is why we chose to apply data mining to discover any such relationship.

After the fractal analysis was completed, data mining was performed on the fractal dimensions. The data mining package Weka[2] was used for the data mining task. First, the fractal dimensions were used to create Weka formatted files. Since the fractal dimensions are continuous real values, these values were converted into discrete categories. The unsupervised attribute discretizer was used for this purpose. It is an entropy-based method that performs discretization using density estimation and computes the leave-one-out

[2]http://www.cs.waikato.ac.nz/ ml/weka



(a) Channel F3 (b) Channel T6

Fig. 4: The fractal dimensions of EEG signals (F3 and T6) measured for two randomly selected subjects in response to a complete music piece split into 30-second segments.

cross-validation log-likelihood of the fit. Five bins were created for the music fractal dimensions and two bins were created for the EEG fractal dimensions.

After the fractal dimensions were discretized, association mining was performed using the *Apriori* algorithm [10] to examine the associations between the fractal dimensions of music segments and the fractal dimensions of resulting multichannel EEG signals. The Weka implementation of *Apriori* was modified to generate rules that only have one antecedent and one consequent, i.e., rules of the form $X \Rightarrow Y$, where $|X| = |Y| = 1$. Moreover, we restricted the antecedent of each rule to consist of a music fractal dimension and the consequent to consist of an EEG fractal dimension. A minimum confidence value of 0.70 was used for association mining.

3.4 Results

The results of the association analysis is presented in Table 1. The first column represents the fractal dimensions of music that associate with the fractal dimensions of multi-channel EEG. The second column represents the fractal dimensions of the EEG with the EEG channel specified in third column. The last column represents the confidence values of the mined association rules. The subjects, who happened to be all female, demonstrated strong association between the fractal dimension of music and fractal dimension of EEG at various EEG channels. Among those, the strongest association was observed between music fractal dimensions in the range of $(2.447-2.546]$ and the EEG fractal dimensions at right temporal lobe (T4 and T6) in the range of >1.854 and >1.864 respectively. This was followed by reasonably strong associations between the same music fractal dimension range and EEG fractal dimensions of >1.947 at left temporal lobe (T5) and EEG fractal dimensions of >1.830 at right frontal lobe (F4) (confidence levels $\geq 88\%$). Strong association discovered in females is an implication that the further research into the association between the fractal dimension of the sound stimuli and the fractal dimension of the EEG may give us a new insight into the selection of effective music in the context of music therapy as an alternative medicine.

Table 1: Results of association mining between the fractal dimensions of auditory stimuli and EEG responses

FD of Music	$\Rightarrow$	FD of EEG	EEG Channel	Confidence
(2.447-2.546]		$>$ 1.854	T4	0.98
(2.447-2.546]		$>$ 1.864	T6	0.94
$\leq$ 2.447		$>$ 1.864	T6	0.93
(2.447-2.546]		$>$ 1.947	T5	0.92
$\leq$ 2.447		$>$ 1.854	T4	0.9
$\leq$ 2.447		$>$ 1.830	F4	0.89
(2.447-2.546]		$>$ 1.881	T3	0.88
(2.447-2.546]		$>$ 1.830	F4	0.88
$\leq$ 2.447		$>$ 1.947	T5	0.87
$\leq$ 2.447		$>$ 1.881	T3	0.86
(2.546-2.644]		$>$ 1.854	T4	0.85
(2.546-2.644]		$>$ 1.864	T6	0.85
$\leq$ 2.447		$>$ 1.927	F3	0.8
(2.546-2.644]		$>$ 1.881	T3	0.8
(2.546-2.644]		$>$ 1.947	T5	0.8
(2.447-2.546]		$>$ 1.927	F3	0.8
(2.546-2.644]		$>$ 1.830	F4	0.76
$\leq$ 2.447		$>$ 1.793	F8	0.7

4. Conclusions

In the present study, we analyzed the fractal dimensions of auditory stimuli and the resulting multi-channel EEG responses. A robust level of correlation between the fractal dimension of the auditory stimuli and the fractal dimension of the EEG was established in female test subjects via association mining. These results had significance at two different levels. First, it implied a promising future of the application of nonlinear analysis of the time-series waveforms in the field of human electrophysiology. Further, it also suggested a significant mathematical association between auditory stimuli in the environment and physiological process in the human body. These implications of our study suggested the importance of further investigations in these two areas. Aside from the needs for further investigation on the significance of the fractal dimension of EEG itself, it is also important to examine the generalizability of present study results to male subjects as well as the generalizability to the use of other forms of auditory stimuli in order to examine the general principles of fractal dimension range of auditory stimuli that produces strong association with a certain range of electrophysiological process in human body. Although the present study was meant to be one case study of the application of data mining methods, the results suggested noteworthy implications in the direction of future research areas in human physiology.

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