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Original Research Article

FRACTAL ANALYSIS FOR ASSESSMENT OF COMPLEXITY OF ELECTROENCEPHALOGRAPHY SIGNAL DUE TO AUDIO STIMULI

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Abstract: Fractal technique has been applied to assess change of brain state when subjected to audio stimuli (in this case a simple music – drone). The Electroencephalography (EEG) time series has been used to perform this study and the corresponding non-linear waveform of EEG was analyzed with the widely used DFA technique. The investigation clearly indicates that FD which is a very sensitive parameter is capable of distinguishing brain state even with an acoustic signal of simple musical structure. Other implications of the results are discussed in detail.

Keywords: Acoustic stimuli, drone, EEG, Brain states, Non-linear analysis, DFA, Fractal dimension

Introduction:

Music engages much of the brain, and coordinates a wide range of processing mechanisms. This naturally invites consideration of how music processing in the brain might relate to other complex dynamical abilities. The tremendous ability that music has to affect and manipulate emotions and the brain is undeniable, and yet largely unexplained. Very little serious research has gone into the mechanisms behind music's ability to physically influence the brain, and the knowledge of the neurophysical effects of music, particularly Indian music. Tanpura is a fretless four string musical instrument tuned to three frequencies. The strings are plucked one after the other in slow cycles of several seconds generating a buzzing drone sound. It has been noticed that the harmonics of the tanpura strings' sound exhibit a periodic waxing and waning. This period is shorter as one goes up along the higher harmonics.[1,2] The periodic change of length in the plucked string creates amplitude fluctuations in the higher harmonics so that the mechanical energy is spread out to very high frequencies.[2,3]

Fractal dimensions of time series data generally reveal the presence of non-linearity in the production mechanism. Tanpura signal is considered as repetitive quasi-stable geometric forms. Time series data is a quantitative record

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of variations of a particular quality over a period of time. The signals emitted by a Tanpura is characterised by varying complexity with undulations of intensity of different harmonics with different frequencies as well as multiple decay. All these suggest interplay of source at various point of time like attack time, quasi-static state and end decay. Non-linear dynamical modeling for source clearly indicates the relevance of non-deterministic approaches in understanding these signals. Study of fractal dimensions have analysed this bevaviour.[4-6] many words have been spoken by various experienced musicians and music listeners about the soothing and calming effect of tanpura drones on mind – but till date only one scientific study has been reported on the subject.[7]

In this context it would be interesting to study the effect of drone on various subjects and study the response to see the effect they produce on each subjects. Since the drone environment is free from semantic and prosodic content, therefore drone might reveal some relative difference in resting between periods of silence and stimulation in the brain pattern. This is because the brain patterns are the subtle expression of mental activity and cognition. Our main focus is on brain-activity measured through electroencephalography (EEG), with electrodes attached to the head cap. We concentrated our study only on the frontal lobe since it is said to be the music sensational area in the brain.[8-11]

In recent years the investigation of brain oscillations has received increasing interest. Many studies have demonstrated that specific cognitive processes are reflected in brain oscillations with characteristic temporal, spatial and spectral signatures.[12, 13] Electroencephalography (EEG) is the neurophysiologic measurement of the electrical activity of the brain by recording from electrodes placed on the scalp or, in special cases, on the cortex. As brain is a complex nonlinear system consisting of thousand of neurons, the EEG data taken is a result of an ensemble of neurons interacting with each other as well as remote neurons whose potentials are not included in measurement. So it is expected that EEG time series might reveal some information about the dynamical properties of the brain. A few papers have been published where support of this expectation was reported.[14,15] The commonly used methods of EEG analysis such as Fourier decomposition are essentially linear, but the complex fluctuations generated by neuronal interactions are not best described by linear decomposition.[16]

Non-linear dynamical analysis has emerged as a novel method for the study of complex systems in the past few decades. The non-linear analysis method is effectively applied to electroencephalogram (EEG) data to study the dynamics of the complex underlying behavior.[17-19] The growth of this method as a tool for mental health evaluation mainly rests on the non-invasive nature of EEG. The approach is based on the principles of non-linear dynamics and deterministic chaos that involves the characterization of the system attractors with its invariant parameters.

For a neuronal network such as the brain, nonlinearity is introduced even on the cellular level, since the dynamical behavior of individual neurons is governed by threshold and saturation phenomena. Moreover, the hypothesis of an entirely stochastic brain can be rejected due to its ability to perform sophisticated cognitive tasks. For these reasons, the electroencephalogram (EEG) appears to be an appropriate area for nonlinear time series analysis techniques, the practical spin-off from the theory of deterministic chaos.[20]

The FD of a waveform represents a powerful tool for transient detection. This feature has been used in the analysis of ECG and EEG to identify and distinguish specific states of physiological function. Many robust algorithms are available to determine the FD of the waveform. There are different methodological approaches and their respective statistical parameters to capture fractality namely Correlation dimension, Lyapunov exponent, Box counting method etc. These are very sensitive to noise and require the stationary condition while EEG signals are highly non stationary. In this paper, we have used a nonlinear method named **Detruded fluctuation analysis (DFA)** to discuss the scaling behavior of the fluctuations in EEG during listening to given stimuli.

DFA is a method for determining the statistical self-affinity of a signal. It is useful for analyzing time series that appear to be long-memory processes (diverging correlation time, e.g. power-law decaying autocorrelation function) or 1/f noise. DFA is known for its robustness against non-stationarity,[21] and by using this method we avoid the assumptions of linearity and low-dimensional chaos. Several previously conducted studies have demonstrated the validity of this method for extracting the scaling properties of the fluctuations in the EEG data.[22,23]

As mentioned earlier, although EEG provides immense information, the widely used methods either fail or miss many crucial features which can reveal surprisingly new results. In this context, fractal analysis is a well developed theory which can be used in the data analysis of EEG time series. More precisely, analysis of chaotic time series in EEG may distinguish specific states of physiological functions. The literature on the study of the application of the nonlinear dynamics theory to analyze physiological signals shows that nonlinear approaches were used for analysis of heart rate, nerve activity, renal blood flow, arterial pressure, EEG and respiratory signals[23-27]. Recently we have reported a number of analyses of EEG data with the help of different nonlinear techniques where it was demonstrated that fractal dimension can be used as a benchmark on the physiological state of the brain – even in diagnosis and prognosis of different neuro-degenerative diseases.[28-30]

In most of the available literature in neuroscience, external stimuli used are mostly visual stimuli such as facial expression, static scenes and film clips to activate brain function.[31-33] However, with audio stimuli (primarily musical) such study is scarce. The importance of audio stimuli (musical stimuli) has recently been felt, not only to understand the emotional structure of the musical sample but more importantly to assess the change of spontaneous electrical activity of the brain deciphering the detailed neural dynamics which eventually can provide information about the secretion of neurotransmitters.[34]

Like other domains, fractal dimension (FD) can be used to characterize the change of brain activity using EEG data with audio stimuli (music).[4,7,9,35-36] In this experiment we have chosen the music stimuli as tanpura drone. 21 subjects listened to the drone sound for two minutes after a no drone condition of two minutes and the change in spontaneous electrical activity of brain was computed by using the robust non linear technique DFA. The listener of Tanpura drone is captivated by its extremely rich harmonic structure. Because there is a felt resonance in perception, psycho-acoustics of Tanpura drone may provide a unique window into the human psyche and cognition.

The result shows the applicability of fractal analysis in this complicated neuroscience domain and a clear picture of brain state in regard to neurodynamics triggered by drone stimuli. The result also shows that while listening to drone the FD may increase or decrease from a small value to a significant one.

Materials and Methods

Subjects Summary:

21 young musically untrained right handed adults (17 male and 4 female) voluntarily participated in this study. Their age was between 20 to 25 years. None of the participants reported any history of neurological or psychiatric diseases, nor were they receiving any psychoactive medication or using a hearing aid. Informed consent was obtained from each subject according to the ethical guidelines of the Declaration of Helsinki. All experiments were performed at the Sir C.V. Raman Centre for Physics and Music, Jadavpur University, Kolkata.

Experimental Details:

The tanpura stimuli given for our experiment was the sound generated using software 'Your Tanpura' in C# pitch and in Pa/Ma (middle octave) — Sa (middle octave) — Sa (middle octave) — Sa (lower octave) cycle/format. The signal was normalized to 0dB and hence intensity or loudness and attack cue are not being considered. Time of each complete cycle was about 4.5 seconds. From the complete recorded signal a segment of about 2 minutes (26 complete cycles) was cut out as per our experimental protocol. Variations in the timbre were avoided as same signal were given to all the participants.

The EEG experiments were conducted in the afternoon (around 2 PM) in an air conditioned room with the subjects sitting in a comfortable chair in a normal diet condition. All experiments were performed as per the guidelines of the Institutional Ethics Committee of SSN College for human volunteer research. Each subject was prepared with an EEG recording cap with 19 electrodes (Ag/AgCl sintered ring electrodes) placed in the international 10/20 system. Impedances were checked below 50 kΩ. The EEG recording system (Recorders and Medicare Systems) was used to record the brain-electrical responses of the subjects at a rate of 256 samples/second with the customized software of RMS. The data was band-pass-filtered between 0.5 and 30 Hz to remove DC drifts and suppress the 50Hz power line interference.

Experimental Protocol:

Since the objective of this study was to analyze the effect of Tanpura drone on brain activity during the normal relaxing condition, the frontal lobe of the brain were selected for the study. EEG was done to record the brain-electrical response of twenty one (21) subjects. Each subject was seated comfortably in a relaxed condition in a chair in a shielded measurement cabin. They were also asked to close their eyes. A sound system (Logitech R _ Z-4 speakers) with very low

S/N ratio was set up in the measurement room that received input from outside the cabin. After initialization, a 4 minute recording was done, and the following protocol was followed:

1. 2 Minutes No drone (eyes closed)
2. 2 Minutes Tanpura Drone (C#) (eyes closed).

Markers were set at start, signal onset/offset, and at the end of the recording. **Figure.1** depicts the position of electrodes on the head.

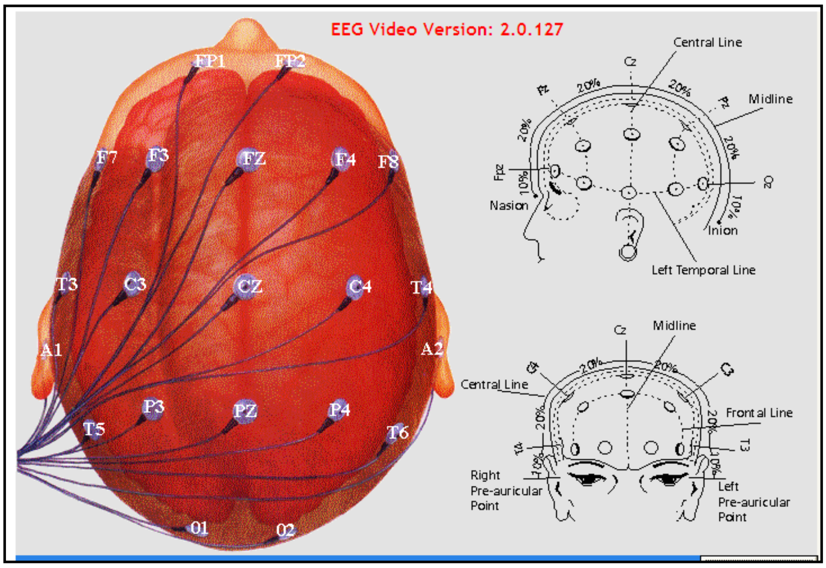

Figure 1: The positions of the electrodes

Methodology:
The raw EEG data obtained from the Computer system was divided in two parts of duration 2 minute each: the first one 'no drone' part and the next 'with drone' part.

Figures. 2 and 3 gives the sample EEG data for a subject in 'no drone' and 'with drone' conditions.

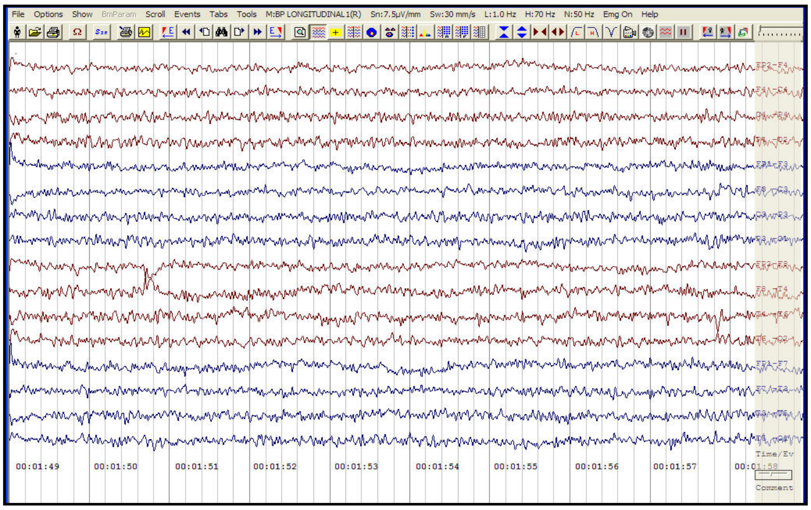

Figure 2: EEG data in 'no drone' condition

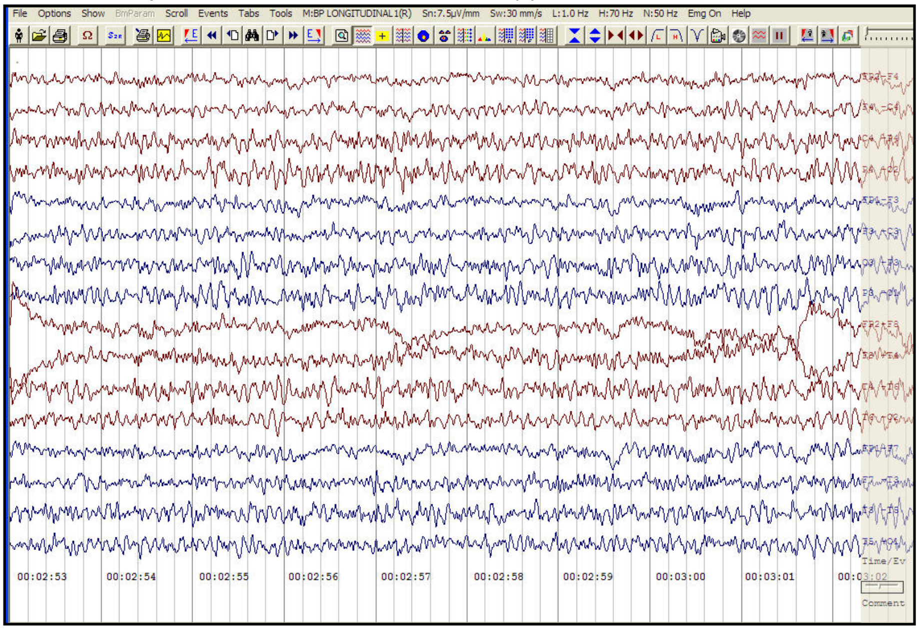

Figure 3: EEG data in 'with drone' condition

From the complete EEG signal of 2 min, we extracted data from five frontal electrodes namely F3, F4, F7, F8 and Fz, since earlier works have demonstrated that responses of the brain in those domains are more pronounced in case of audio stimuli.[8-11] Detrended Fluctuation Analysis (DFA) technique proposed by Peng et.al[37] was employed on the time series data of each electrode using open source software module PyEEG,[38]for the two experimental conditions, to calculate the fractal dimensions of the waveforms.

The procedures to compute DFA of a time series $[x_1, x_2,...,x_N]$ are as follows.

(1) First integrate x into a new series y = [y(1),...,y(N)], where $y(k)=\sum_{i=1}^{k}(x_i - \bar{x})$and $\bar{x}$ is the average of $x_1,x_2,...,x_N$.

(2) The integrated series is then sliced into boxes of equal length n. In each box of length n, a least-squares line is fit to the data, representing the trend in that box. The coordinates of the straight line segments are denoted by y_n(k).

(3) The root-mean-square fluctuation of the integrated series is calculated by F(n)= $\sqrt{(1/N)\sum_{k=1}^{N}[y(k)-y_n(k)]}$, where the part [y(k)− y_n(k)] is called detrending.

(4) The relationship between the detrended series and interval lengths can be expressed as $F(n) \propto n^{\alpha}$ where α is expressed as the slope of a double logarithmic plot log [F(n)] versus log(n). The parameter α (scaling exponent, autocorrelation exponent, self-similarity parameter) represents the autocorrelation properties of the signal.[37] It can be converted into the Hurst exponent **H = α –1** and Fractal dimension (FD) accordingly as $\mathbf{D_{DFA}= 3 - \alpha}$.[22]

In order to eliminate all frequencies outside the range of interest, data was filtered with a 1-30 Hz filter. The variation of FD (using the technique DFA) with time were found out for 'No drone' and 'with drone' conditions.

Results and Discussions:

The scaling exponent α was computed from the linear fit of log-log plot for all the subjects. **Figures.** 4 and 5 are double logarithmic plot of log F(n) vs log n for a sample subject in the aforementioned two experimental conditions for the electrode F3.

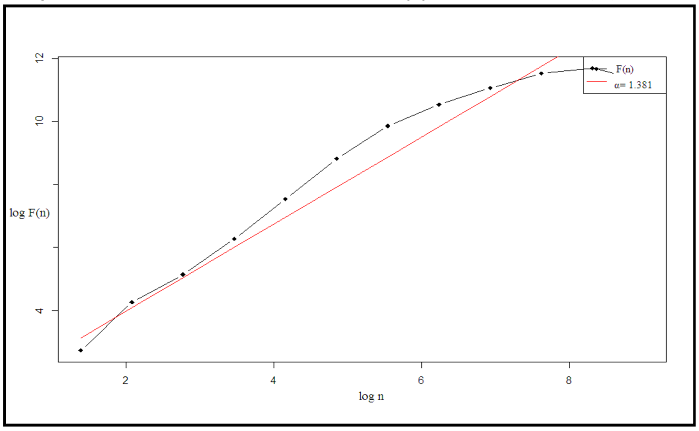

Figure 4: Scaling exponent from a sample log-log plot in ‘no drone’ condition for F3

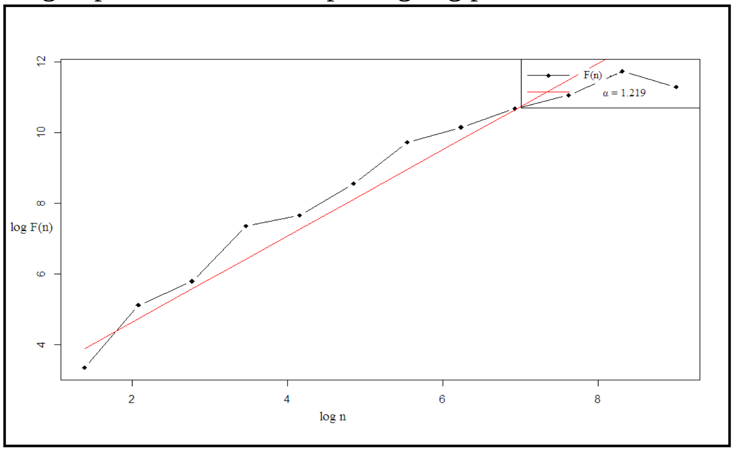

Figure 5: Scaling exponent from a sample log-log plot in ‘with drone’ condition for F3

The scaling exponent provides a quantitative measure of long range temporal correlation (LRTC) that exists in the EEG. When the EEG is completely uncorrelated (Gaussian or non-Gaussian probability distribution), the calculation of the scaling exponent yields 0.5, also called “white noise”. When applied to EEG data with LRTC, power-law behavior will generate scaling exponents with greater than 0.5 and less than 1. As the scaling exponent increases from 0.5 to 1, the LRTC in the EEG are more persistent (decaying more slowly with time). If a scaling exponent is greater than 1, the LRTC no longer exhibits power law behavior. Finally, if the scaling exponent = 1.5, this indicates Brownian noise, which is the integration of white noise.[39]

In our case, the value of α range between 0.5 and 1 in most of the cases, while for a few the value ranges between 1 and 1.5. This quantifies the presence of LRTC in all the EEG data in use. Also, for all the subjects we have noticed a change in long term temporal correlation when the tanpura drone as stimulus is administered.

For each subject, fractal dimension (FD) was computed for the waveforms obtained from different frontal electrodes namely F3, F4, F7, F8 and Fz from the scaling exponent ‘α’, following the algorithm of Peng.et.al.[22]

Table 1 gives a detailed account of the variation of FD values for ‘no drone’ and ‘with drone’ conditions (both of them were recorded in eyes closed condition) of all the five frontal electrodes for 21 subjects. Also, the average values of FD for the frontal electrodes in both the experimental conditions are shown. From these average values, the difference in FD values for each of the subjects has been calculated.

Table 1: Variation of FD values for 21 subjects on application of drone as stimulus

	Fractal Dimension												
Sub No.	No drone (N.D)						With drone (D)						
	F3	F4	F7	F8	Fz	Average frontal	F3	F4	F7	F8	Fz	Average frontal	Change (D - N.D)
1	1.741	1.749	1.995	1.789	1.733	1.801	2.053	2.033	2.093	2.036	1.944	2.032	0.231
2	1.969	1.811	1.831	1.953	1.934	1.9	1.948	1.961	1.914	1.95	1.954	1.945	0.045
3	1.844	1.857	1.916	1.896	1.861	1.875	1.846	1.855	1.917	1.884	1.874	1.875	0
4	2.147	1.974	2.169	1.938	1.961	2.038	2.04	1.938	2.049	1.979	1.937	1.989	-0.049
5	2.03	1.895	1.982	1.895	1.926	1.946	2.085	1.912	2.149	2.016	1.936	2.02	0.074
6	1.876	1.901	2.001	1.949	1.898	1.925	1.756	1.914	2.023	1.758	1.811	1.852	-0.073
7	1.882	1.837	1.722	1.908	1.901	1.85	1.731	1.835	1.661	1.823	1.724	1.755	-0.095
8	2.195	2.038	2.197	2.077	2.175	2.136	2.139	1.886	1.897	1.889	2.124	1.987	-0.149
9	2.065	2.224	2.104	2.307	2.154	2.171	2.229	2.322	2.317	2.352	2.243	2.293	0.122
10	2.141	2.082	2.116	2.09	2.235	2.133	2.283	2.208	2.2	2.173	2.289	2.231	0.098
11	2.219	2.247	2.185	2.363	2.097	2.222	2.171	2.154	2.187	2.238	2.14	2.178	-0.044
12	1.835	1.861	1.866	1.882	1.836	1.856	2.175	2.224	2.109	2.127	2.298	2.187	0.331
13	2.123	2.157	2.085	2.133	2.202	2.14	2.255	2.298	2.119	2.154	2.372	2.24	0.1
14	2.352	2.347	2.378	2.339	2.371	2.357	2.301	2.273	2.268	2.253	2.295	2.278	-0.079
15	2.336	2.267	2.245	1.888	2.308	2.209	2.319	2.334	2.334	1.966	2.403	2.271	0.062
16	2.372	2.374	2.365	2.156	2.344	2.322	2.304	2.282	2.299	1.884	2.303	2.214	-0.108
17	2.334	2.353	2.27	1.905	2.252	2.223	2.216	2.256	2.181	2.203	2.244	2.22	-0.003
18	1.824	1.883	1.869	1.861	1.826	1.853	2.09	2.542	2.125	2.085	2.074	2.183	0.33
19	1.963	1.979	1.992	1.991	1.961	1.977	1.95	1.95	1.981	2.008	1.943	1.966	-0.011
20	2.294	2.266	2.295	2.287	2.315	2.291	2.033	2.003	2.123	2.193	2.001	2.071	-0.22
21	2.455	2.457	2.442	2.439	2.48	2.455	2.369	2.412	2.38	2.433	2.396	2.398	-0.057

Conclusions:

The following observation comes out from the analysis of data:

1. After input of audio stimuli (simplest music as already mentioned) the value of FD for the same 21 subjects on the same electrodes changes (except for one), but there are two distinctive groups (subjects) in regard to the change of FD – in one case FD decreases (Group 1) while in other case FD increases (Group 2).
2. The amount of change of FD value ranges from 0.003 to 0.220 for Group 1 (i.e. in case of decrease) whiles for Group 2 (i.e. in case of increase) the change of FD value ranges from 0.045 to 0.331.
3. This analysis clearly indicates that FD which is a very sensitive parameter is capable of distinguishing brain state even with an acoustic signal of simple musical structure.

It deserves mentioning that conventional linear techniques using Fourier transform or power spectra are unable to decipher this level of change of brain state recognition due to its intricate complex waveform.

In view of above findings, a clear picture of brain state in regard to recognition of audio stimuli emerges which speaks in contrary to conventional wisdom – while listening to music (here drone) the FD (or the complexity or the indication of degree of chaos) may increase or decrease from a small value to a significant one

Moreover, earlier works concentrated on only theta (4-8Hz) and alpha range (8-12 Hz),[8,9,17,35-36] whereas this study can justifiably accommodate the real electrical activity of the brain in different spatial domains. We may conclude that this paper shows the applicability of fractal analysis in this complicated neuroscience domain, which was our primary objective in this analysis.

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