Studying emotion through nonlinear processing of EEG

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Abstract

In this article we study the effects of emotion on brain activity through nonlinear processing of EEG. EEG was recorded from 19 sites (10-20 systems) in different states of brain activity; induced by emotionally valence music stimulus and also during no-task resting states. Then, we compared the EEG complexity of the rest condition with each emotional states. After that we determined the locations in which correlation dimension was changed in different states through one-way ANOVA test. In this study four excerpts of music from both Iranian traditional music and Western classical music, two negative valance and two positive valance pieces, were selected according to the results of Psychological papers.

1. Introduction

Undoubtedly emotions play an important role in human life. So, in recent years, studying brain activities during emotional experiences has increased. Even psychologists have difficulties agreeing on what is an emotion and what types of emotions exist. Emotions have been described in terms of both discrete and dimensional. Based on the discrete perspective of emotions, there are unique physiological and behavioral profiles for each emotion like anger, happiness, etc. In contrast, the dimensional perspective of emotions contends emotional states are organized at least by two factors, valance (positive/negative) and arousal (calm/exciting). Although dimensional and discrete perspectives can be reconciled to some extent, most researches and also this study use the dimensional model of emotions because it can describe emotional states better than the other model (Mauss & Robinson, 2009).

The goal of this research is to study the effect of emotion on brain activity. Although most of the published papers in this area have used visual stimuli in order to induce emotion, in this study we used music because, based on other research, music is one of the most powerful elicitors of subjective emotion (Baumgartner, Esslen, & Jancke, 2006). fMRI results also show that brain areas which are known as emotion centers, are activated during listening to music (Limb, 2006). For this purpose, we recorded EEG which is rich in information on brain activity.

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We can achieve global information about mental activities during emotional states through proper signal processing of EEG.

Most researchers have calculated power spectrum in different frequency bands especially alpha power which is thought to be inversely related to regional cortical activation. It was recently estimated that over 70 published EEG studies report greater relative left frontal activity associated with positive emotions, while greater relative right frontal activity was associated with negative emotions which is termed as "frontal asymmetry". These studies have established differential roles of left and right prefrontal cortex for processing pleasant and unpleasant emotional information, respectively (Herrington et al., 2010). But common traditional methods of physiological time series analysis which focus on time domain statics, frequency or frequency-scale domain are useful for linear systems with very specific mathematical properties e.g., linear, stationary, Gaussian distributed. To date, it is obvious that biological systems such as brain are inherently complex, non-Gaussian, nonlinear, and non-stationary (Paraschiv-Ionescu & Aminian, 2009). The most important thing in these systems is the interactions among components. So to understand the behavior of these systems, it is imperative to perceive not only the behavior of its components, but also the logic of interactions among the components. That is why nonlinear time series analysis has emerged as a novel methodology over the past few decades, which makes it possible to extract progressively more meaningful information from the recordings of brain activity (Stam, 2005). Recent theories of complex systems and nonlinear dynamics have suggested strategies where the focus shifts from the traditional study of averages, histograms and simple power spectra of physiological variables to the study of the pattern in the fluctuations of variables using nonlinear analysis methods (Paraschiv-Ionescu & Aminian, 2009). One approach to nonlinear time series analysis consists of reconstructing, from time series of EEG, an attractor of the underlying dynamical system, and characterizing it in terms of its dimension. Unlike most of the studies in this area, we used nonlinear analysis, correlation dimension method, to achieve meaningful information from EEG.

2. Data Collection

2.1. Subjects

Five right handed healthy females participated in this study. All participants were Master students of Biomedical Engineering at Amirkabir University of Tehran; they were between the ages of 22 to 25 years old. They didn’t have any physiological problems or psychological disorders and also they weren’t expert in music art. All of the states of experiments had been explained for them before recording EEG. We wanted them not to be weary or involving in stressful and exciting difficulties. All the experiments were done between one Pm and three Pm.

2.2. Stimuli

Two tracks of the selected music were derived from the results of a psychological paper in which the effects of seven Iranian musical instruments on Iranian people were discussed. We selected two pieces of music with the most positive and negative valance from Mahoor and Nava (Nazari et al., in press). The other two tracks were selected similarly, from another psychological paper which discussed effects of western classical music on western people (Krumhansl, 1997). The musical stimulus instrument consisted of excerpts of exactly 60 seconds duration.

2.3. Procedure

All participants kept their eyes closed and sat on the comfortable chairs with no significant movements during the entire emotion elicitation experiment. The experiment began by looking at one picture with purpose of decreasing excitements and stressful tensions for 90 seconds. After that EEG was recorded for 60 seconds as their eyes were closed and without listening to music. Then Mahoor, Nava, western classical track with positive valance and western classical track with negative valance were played respectively and during each piece of them EEG was recorded.

Although the songs had been selected from psychological papers, because of individual differences among volunteers, after playing a piece of music we asked them to assess their emotional valance and arousal that they had experienced during listening to music. To this purpose we used Self-Assessment Manikin method, which is a non-verbal pictorial assessment technique that directly measures the valance, arousal, and domination associated with a person’s affective reaction to a wide variety of stimuli. Based on subjects’ self assessment, we categorized subjects in two groups, negative valance and positive valance. In both groups, they had the most negative and positive
emotional valance. It is worth mentioning that after assessing emotional states, enough time to return to the rest state was given and next track was played when they were ready.

2.4. EEG measurement

EEG data was captured by a 19-channel EEG module, where the scalp locations were relevant to the international 10-20 system. A1 or A2 was the reference electrode. Sampling rate was 1024 and recorded frequency bandwidth was 1 to 70 Hz. It’s significant that in this experiment no preprocessing were executed, because the filter’s phase has nonlinear manner and that nonlinear behaviors cause malfunction in natural trajectory of the signal. However, unlike the common methods in signal processing, phase of the signal is the most important factor. In fact phase of the signal is more important than amplitude of the signal for us.

3. Nonlinear processing

As we know, in such studies we do not have a set of differential equations. We only have a set of observations in the form of EEG record, as a starting point (Stam, 2005). Since the nature of underlying dynamics and its properties are anonymous to us, to obtain a better understanding of dynamics of the system we used nonlinear time series analysis. The first and the most decisive step in nonlinear analysis is to reconstruct from time series of observations an attractor in the state space of the underlying system. The most utilized method of reconstructing the full dynamics of the system from scalar time measurements is based on the embedding theorem which states that we can ‘reconstruct’ the attractor of the system from the original time series and its time-delayed copies as is mentioned below (Hegger, Kantz, & Schreiber, 1999; Paraschiv-Ionescu & Aminian, 2009):

\[ X(i) = [x(i + \tau), x(i + 2\tau), \ldots, x(i + (m - 1)\tau)] \]

Where "X(i)" is the state vector, "m" is the embedding dimension and "\tau" is the time delay. So vector "X(i)" which defines a point in the phase space, represents the state of the system at any moment. Since dynamical properties of the system will be achieved through analysis of reconstructed attractor, to determine about the correct value for two parameters, "m" and "\tau" are one of the most important steps in reconstructing the attractor. Taken has proven that if embedding dimension, "m", is large enough (\( m \geq 2d + 1 \): more than twice the dimension of the systems attractor), the reconstructed attractor will be equivalent to the exact attractor of the system and their properties will be identical. If the systems delay having the amount that is larger than applied margin, the system at the time "t + \tau" doesn’t have relatively any association with the state of the system at the point "t", and we can conclude that the system has forgotten its own state. So dynamical association of the system and also its interactions have become lost. In other word, with selecting great delay the information structure of the system became defunct and accessing the interactions between the constructing points of the system, is not possible. By selecting less value of the "\tau" parameter toward the dynamic time series velocity, the system doesn’t have enough time during this step to change its own condition. So reconstruction will faced with little delay and has a time information redundancy about one.

There are several methods to find the best time delay; such as the position of the first local minimum of the autocorrelation function of data and first minimum of average information reciprocal function, which evaluate the amount of information shared between two data sets over a range of time delays. While the first approach considers only linear relations between two data sets, the method of reciprocal information evaluates also nonlinear signal structures. So we also used the first minimum of average mutual information function to compute the best time delay to reconstruct the attractor. In addition there are several methods to determine the embedding dimension. One of the most useful procedures is false neighbours method. But in this study, based on the scale invariance property of physiological systems, we computed the best embedding dimension as well as the correct correlation dimension. This method is explained as follows.

3.1. Correlation dimension and its concepts

To characterize the reconstructed attractor, the correlation dimension was computed for every 19 channel in each state, which is conventionally termed as EEG dimensional complexity and yields the meaningful information regarding the complexity of computations in the brain. In fact, the correlation dimension shows the amounts of the independent variables required to exhibit the behaviour of the system. The most frequently useful algorithm for
calculating correlation dimension was introduced by Grassberger and Procaccia. This algorithm is based upon the correlation integral (Cr). In this algorithm, after reconstructing the attractor, the distance between each pair of points in the state space is calculated and Cr is determined as follows:

\[
C_m(r) = \frac{2}{N-(m-1)!} \sum_{j=m}^{N-m-w+1} \sum_{k=j-w}^{N-m} \Theta(r - \|X_j - X_k\|)
\]

(2)

Where \(\Theta\) defined as below:

\[
\Theta(x) = \begin{cases} 
1 & \text{if } x \geq 0 \\
0 & \text{if } x < 0 
\end{cases}
\]

(3)

The correlation integral is computed in a wide range of "r". Then "Cr" is plotted as a function of "r" in a double logarithmic plot. After some time with increasing "r", significant change didn’t occur in "Cr" and the curve goes to the saturation region. There is a deep concept based on the fractal properties in this step which is explained below.

As we know the fractal was not considered until Benoit Mandelbrot announced that this geometry is useful to describe complex structures of the nature. Fractals have self-similarity properties. Accordingly, they are scale invariance and their properties do not change if the length criterion is multiplied by a common factor. So the larger parts and the smaller parts have identical properties. It means we can find properties of the system through analyzing a small part of the signal. This property in fractal structures is found in a region which is named scaling region. Power law is established in this region and is any polynomial relation that exhibits the property of scale invariance. Power law expresses that, if a slight parameter like "q" is measured by a parameter, named "s", and it represents the scales, have a relationship with each other like "q = f(s)" , in Fractal process, power law has a scale of "q = p.s^ε" between "q" and "s" parameters, in which "p" is a factor and "ε" is a negative number that is named as scale index. We can simply calculate the amount of "ε" by using fitted slop line of the data log(q) to log(s) (log(q) = log(p) + ε log(s)).

So if we plot "Cr" as a function of "r" in a double logarithmic plot, there will be a region with linear slope (scaling region) in which the power law exists (\(Cr \approx r^D\)). The slope of this region is an estimation of the correlation dimension. Proper recognition of this region is the most important step in this algorithm, but there is not an automatic method to determine the scaling region. It is significant that in this study we found the best amount of embedding dimension based on scale invariance property of the fractals too. As we mentioned above their properties do not alter by changing in sizes. In other words information doesn’t change by increasing or decreasing dimension. We can use this concept to find the best embedding dimension that can explain all the information about the dynamic of the system. So we computed the embedding dimension as well as correlation dimension which is explained below.

3.2. Automatic method

For more clarification we use some examples in the following. As mentioned above we can determine a point in the curve of log(Cr) to log(r) at which the curve goes to saturation region (a.) as is shown in fig 1. Assume "a_1" point as a starting point of the algorithm. Then we fitted a line to this point and three points prior to it (that locates out of saturation region), that are named as "a_1", "a_2", "a_3", "a_4". After that, we compared RMSE\(^\dagger\) of this line with our desirable RMS criterion. If RMS factor of the line is less than our desirable amount, then we add the next point. It means that we fitted line to the points: "a_1", "a_2", "a_3", "a_4", "a_4". Otherwise, we calculate the slope of fitted line to the "a_1", "a_2", "a_3", "a_4"points, and after that we do the same procedure for a_2 and prior points to it, "a_2", "a_3", "a_4", "a_5". This procedure should be done for all points of log(Cr) to log(r) curve. Note that all of these procedures should be calculated individually for each embedding dimension.

In the next step, plot the embedding dimension curve to obtained slopes. To this point, each of the characterized area in embedding dimension would be the proper scaling region. For finding the correct scaling region we use the suggested context of previous sections. As it was said, if non-associated property of the system information to the size or dimension of the system is indefeasible in scaling region, by increasing in embedding dimension, correlation

\(^\dagger\) Root mean square method
dimension shouldn’t alter as a property of system information. Therefore, if the correlation dimensions curve to the embedding dimension goes to saturated region, we have recognized correctly the scaling region.

To find the saturated region, we started from embedding dimension 30. We consider the slopes that are gained from embedding dimension 30 and calculate distance between each one of these slopes to the embedding dimension slopes of 29. If these two dimensions are located in the saturated region, the desirable amounts of the slopes should be very close to each other. So we set the slopes of these two embedding dimensions in such a way that they have the least distance from each other. We choose some sets of combinations that are the best. We do the same procedure on the embedding dimension 28, toward the average selected slopes amounts in each set of combinations for embedding dimensions 29 and 30 and do this procedure again and again.

Between these points we search for the best saturated area, and also we search for the reference point in which the curve is going to the saturated region. Because when correlation dimension reaches the saturation amount, the associated quantity of it, is considered as the optimum estimation for embedding dimension, and we can consider the amount of correlation dimension in it, which is known as correlation dimension and scale of the system complexity. For this purpose, we should calculate variance for each set of selected points in the dimensions 28, 29 and 30. So we have an estimation of these dispersal three points, around their average amount. If in a set of points, we face larger variance than 0.002, we eliminate that set of points and in the remaining sets of points we calculate the variance amount in the dimensions of 27, 28, 29 and 30. We do the same procedure on the remaining sets of points so that only one set of points remains; by adding embedding dimension to them. Whenever we obtain larger amounts of variance than 0.002, we set that point as a saturated reference point as is shown in Fig 2.

4. Results

First to reduce arithmetic operations, we computed correlation dimension for 10 second length of EEG. Then, to investigate the effect of the number of points on correlation dimension, we chose another different length of EEG, 21s, and computed correlation dimension again. For the values of correlation dimension in each channel, repeated measures ANOVAs were computed (rest, negative valance and positive valance). The results indicate significant
differences (p-value< 0.05) between two states of rest and positive valance emotion in 3 channels: F3, T3, Fz and between two states of rest and negative valance emotion in 3 channels: Fp2, C4, P4. And also in these channels correlation dimension has decreased in emotional states in comparison with the rest state. We obtained similar results with 21 seconds of EEG. Results are shown in tables 1, 2, 3, 4.

### Table1. Correlation dimension, length of EEG is 10s

| Channels | Rest state | negative valance | p-value |
|----------|------------|------------------|---------|
| Fp2      | 8.37±0.26  | 7.36±0.69        | 0.472   |
| C4       | 8.44±0.23  | 7.17±0.49        | 0.0107  |
| P4       | 8.106±0.1  | 7.037±0.27       | 0.004   |

### Table2. Correlation dimension, length of EEG is 10s

| Channels | Rest state | Positive valance | p-value |
|----------|------------|------------------|---------|
| F3       | 8.41±0.41  | 6.86±0.68        | 0.0077  |
| T3       | 8.011±0.41 | 6.94±0.58        | 0.041   |
| Fz       | 8.54±0.27  | 6.99±0.29        | 0.0018  |

### Table3. Correlation dimension, length of EEG is 21s

| Channels | Rest state | negative valance | p-value |
|----------|------------|------------------|---------|
| Fp2      | 8.3612±0.75| 6.50336±0.28     | 0.003569|
| C4       | 8.5384±0.25| 7.20854±1.06     | 0.03759 |
| P4       | 8.222±0.19 | 6.50836±0.12     | 0.000118|

### Table4. Correlation dimension, length of EEG is 21s

| Channels | Rest state | Positive valance | p-value |
|----------|------------|------------------|---------|
| F3       | 8.208±0.45 | 6.71456±0.36     | 0.006328|
| T3       | 7.804±0.05 | 6.66814±0.57     | 0.012282|
| Fz       | 7.9436±0.18| 6.6533±0.18      | 0.00527 |

### 5. Conclusion

Based on the findings of others an optimal level of dimensional complexity should exist for the maximum performance of a given task. Increasing dynamical complexity, up to a certain level, may be a necessary precondition for generating emotion. In our study, too, we observed that the correlation dimension decreased in emotional experience in comparison with the rest states. In fact, the task performance reduces the dimensional complexity in those areas in which networks became engaged actively, so it seems that the brain areas equivalent with those channels are affected through the emotional conditions. Lower correlation dimension estimates in our results during emotional experience vs. rest may indicate a more active involvement of those regions during emotional experience. In addition, similar results for two different lengths of EEG represent the fractal property of EEG.
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