

Quantification of emotion by nonlinear analysis of the chaotic dynamics of electroencephalograms during perception of $1/f$ music

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Abstract. The goal of this study is to quantify and determine the way in which the emotional response to music is reflected in the electrical activities of the brain. When the power spectrum of sequences of musical notes is inversely proportional to the frequency on a log-log plot, we call it $1/f$ music. According to previous research, most listeners agree that $1/f$ music is much more pleasing than white ($1/f^0$) or brown ($1/f^2$) music. Based on these studies, we used nonlinear methods to investigate the chaotic dynamics of electroencephalograms (EEGs) elicited by computer-generated $1/f$ music, white music, and brown music. In this analysis, we used the correlation dimension and the largest Lyapunov exponent as measures of complexity and chaos. We developed a new method that is strikingly faster and more accurate than other algorithms for calculating the nonlinear invariant measures from limited noisy data. At the right temporal lobe, $1/f$ music elicited lower values of both the correlation dimension and the largest Lyapunov exponent than white or brown music. We observed that brains which feel more pleased show decreased chaotic electrophysiological behavior. By observing that the nonlinear invariant measures for the $1/f$ distribution of the rhythm with the melody kept constant are lower than those for the $1/f$ distribution of melody with the rhythm kept constant, we could conclude that the rhythm variations contribute much more to a pleasing response to music than the melody variations do. These results support the assumption that chaos plays an important role in brain function, especially emotion.

inherent in the artistic and subjective nature of the musical experience. Listening to music is a very personal experience determined by many factors, such as personality, interest, education, learning, culture, and so on. In spite of its universality among cultures, music is not a biological necessity, and there are very large variations in musical sensitivity and ability among people (Meyer 1956). Music perception is, therefore, a human activity that does not easily lend itself to scientific experimental inquiry, which usually requires an overt response that can be quantified and which relies on group homogeneity for generalization. Hence, we know little about how the physical features of acoustic stimuli are processed to form psychological representations of the sound and how knowledge about sound contributes to sensory integration and percept formation.

Some research on $1/f$ noise has given us insight into overcoming the difficulties in the scientific study of music perception and understanding the origin of the universal emotional response to music (Voss and Clarke 1975, 1978; Schroeder 1991; Gardner 1992). When the power spectrum of a time signal is inversely proportional to frequency on a log-log plot, we call it a $1/f$ distribution. According to Voss and Clarke, the power spectra of the loudness and frequency fluctuations for Bach's music, averaged over the piece, have $1/f$ distributions (Voss and Clarke 1975, 1978). Not only Bach's work, but also other works of classical music, jazz, blues, and rock have $1/f$ power spectra (Voss and Clarke 1975). This means that our musical pleasure depends not so much on the absolute value of the pitch or the tone duration or the loudness, as on how it changes as a function of time. This is because the power spectrum of a time signal is a Fourier transform of its autocorrelation, which measures how its fluctuations at any moment are related to previous fluctuations. In addition, Mandelbrot showed that aesthetic structures throughout nature and artistic works have fractal structures (self-similarity) that are related to $1/f$ distributions (Schroeder 1991; Gardner 1992).

Based on these studies, we decided to estimate the relative changes of the brain states elicited by $1/f$ music, which is pleasing, and by white music and brown music,

1 Introduction

Understanding the functional mechanism of music perception is lagged with a wide variety of difficulties

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which are less pleasing. White music involves a sequence of musical notes (e.g., the successive frequencies of a melody) which is completely independent of its past (Schroeder 1991; Gardner 1992). Its autocorrelation function is zero, except at the origin where it must be 1, and its power spectrum is flat over the entire frequency range. White music has few correlated sequences, so we cannot predict the next note from the previous ones. By contrast, brown music has highly correlated sequences (Schroeder 1991; Gardner 1992). Only the increments are independent of the past. It has characteristics of Brownian motion, the random movements of small particles suspended in a liquid and buffeted by the thermal agitation of molecules. Finally, $1/f$ music has a degree of correlation intermediate between white and brown music (Schroeder 1991; Gardner 1992). Its tunes are moderately correlated, not just over short runs but throughout runs of any size. Voss and Clarke confirmed that $1/f$ music was judged by most listeners to be much more pleasing than white music (which is too random) or brown music (which is too correlated) (Voss and Clarke 1975, 1978). White music has a power spectrum of $1/f^0$, and brown music has a power spectrum of $1/f^2$. In order to study the universal emotional response to music, $1/f$, white, and brown music were generated by a simple computer program, independent of the characteristics of musical instruments, culture, and past personal experiences. Also, the subjects in our experiment were all non-musicians. For the study, we developed a simple algorithm to determine the pitch (expressed in various standard scales) and the duration (expressed as half, quarter, or eighth notes) of the successive notes of a melody.

A nonlinear analysis of an electroencephalogram (EEG) was used to quantify the emotional change of the brain in our study. The brain is a highly nonlinear and very chaotic system. In addition, research with nonlinear methods has revealed that the EEG is not a simple noise, but a deterministic chaotic signal (Rapp et al. 1985; Babloyantz 1986; Başar 1988; Röschke and Başar 1988; Soong and Stuart 1989; Röschke and Aldenhoff 1991; Ravelli and Antolini 1992; Fell et al. 1993). Furthermore, it has been shown that distinct states of brain activity have different chaotic dynamics, which can be quantified by nonlinear invariant measures such as the correlation dimension and the largest Lyapunov exponent. Linear spectral analysis may not clarify the basic mechanism of complex brain function, although it has worked well in a clinical environment for several decades.

Freeman suggested that chaos plays an important role in olfactory information processing in the brain (Freeman 1991). When an animal inhales a familiar scent, a burst can be seen in each EEG tracing. Afterwards, all the waves from the array of electrodes suddenly become more regular and ordered for a few cycles until the animal exhales. His studies suggested that nonlinear analysis of an EEG should be a good tool for understanding the mechanism of perception.

Birbaumer et al. estimated the pointwise dimensions of an EEG during perception of periodic, weakly cha-

otic, and stochastic music similar to the music in our experiments (Birbaumer et al. 1994). Their study showed that the low-dimensional chaotic music induced a reduction of the EEG dimension, mainly in the frontal electrodes, compared with the periodic and stochastic music. Their results, however, are somewhat different from ours. We found meaningful correlations between chaotic brain activities at the right temporal electrode and different types of music. We calculated two nonlinear invariant measures of the EEGs, the correlation dimension and the largest Lyapunov exponent, in our analysis (Takens 1981; Grassberger and Procaccia 1983; Babloyantz and Salazar 1985; Eckmann and Ruelle 1985; Wolf et al. 1985; Fraser and Swinney 1986; Theiler 1986; Smith 1988; Dvořak and Klaschka 1990; Kennel et al. 1992; Ott 1993). They are effective measures for the complexity and the chaos of the EEG, respectively. In particular, the correlation dimension is a measure of complexity. While periodic and quasi-periodic systems have integer correlation dimensions, a system with deterministic chaos has a noninteger dimension (fractal). The Lyapunov exponents estimate the mean exponential divergence or convergence of nearby trajectories in phase space. A system possessing at least one positive Lyapunov exponent is chaotic. This fact reflects a sensitive dependence on initial conditions.

In Section 2, we present the algorithm for generating $1/f$, white, and brown music. How to reconstruct brain dynamics from the EEG and to analyze the EEG by using nonlinear methods is given in Section 3. The algorithms for the correlation dimension and the Lyapunov exponents are also presented. Section 4 briefly presents the procedures for data recording and for the experiments. Section 5 shows the difference in the values of the correlation dimension and the largest Lyapunov exponent of EEG for the different types of music. We discuss our results with respect to the role of chaos in emotion during music perception in Section 6. Our conclusions are given in Section 7.

2 Computer-generated music: $1/f$, white and brown music

A computer program with the following algorithms, proposed by Gardner (1992), was designed to produce musical stimuli with different spectral densities. The different musical stimuli were produced according to a sequence of numbers selected by tossing imaginary dice successively.

1. White music. We need only one imaginary die with 120 sides to produce white music. We successively throw the die. The sequence is made from the selected number on the die. Each value has the same probability of $1/120$ of being chose, and one quantity is not affected by any of its preceding quantities.

2. Brown music. The first note, say middle C, is determined by a random number generator. The next note of the pitch, or the duration, for brown music is determined by throwing a die with three sides (+1, 0, -1). For +1, the fluctuating quantity (pitch or duration) in-

creases by one step. For 0, it stays the same, and for -1 , it decreases one step. In this way, we produce successive quantities that are highly correlated over long periods of time.

3. $1/f$ music. We use twenty dice, each with six sides, to produce $1/f$ music. First, we throw all twenty dice and calculate their sum. For the next trial, we randomly choose seven dice and throw only those chosen dice again. We recalculate the sum of all twenty dice; then, we repeat the procedures as many times as we like. The resulting sequence of sums has a correlation about half-way between those of white and brown music.

The pitch range in the computer-generated music was 3 octaves, with the fundamental frequencies of the tones falling roughly in the range of 100 to 8000 Hz. The duration was between 0.1 and 2 s.

The wave patterns for these processes are shown in Fig. 1. Since two variables were needed to identify each note (its pitch and tone duration), two sequences were made and then combined to produce each musical stimulus. With the program, it was possible to choose

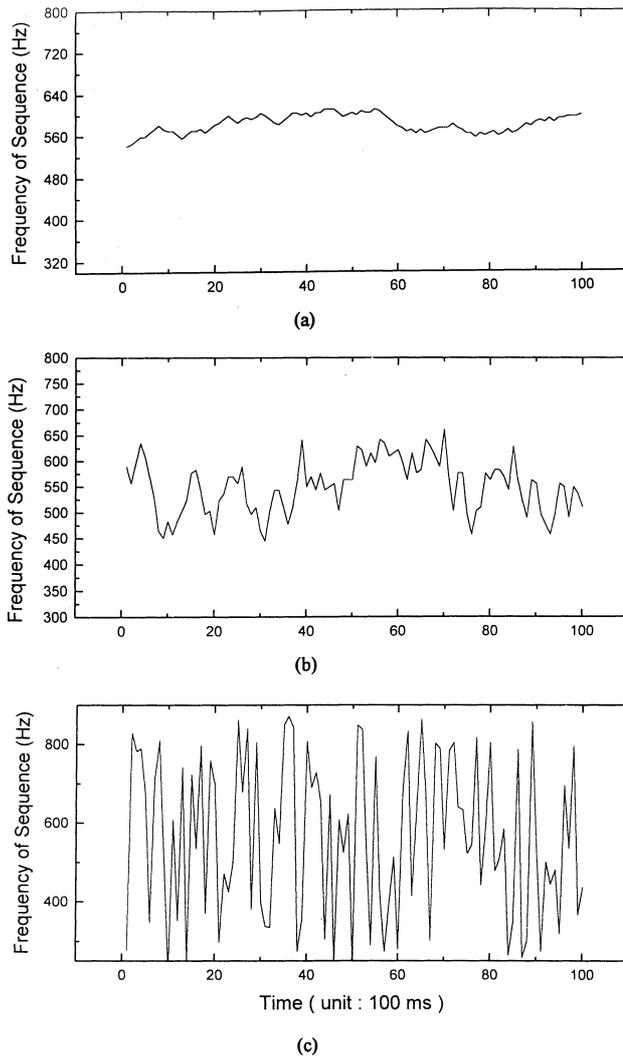


Fig. 1. Wave patterns of (a) brown, (b) $1/f$, and (c) white music as a function of time

the type of variation or the range of the pitch/duration (melody/rhythm) and to make as many combinations as needed.

To verify whether the programmed music could be considered as $1/f$, brown, or white music, samples of 7200 data points for each type of music were plotted (spectral density vs frequency) on a log-log graph. It was found that each form could be characterized by the value of the slope: $1/f$ music had a slope of -1.032 , white music a slope of -0.019 , and brown music a slope of -1.850 . The spectral density was a measure of the mean-square variation of a quantity. The slope of the log-log plot was estimated by the least-squares method to quantify the degree of correlation over successive notes. In general, a negative slope for spectral density implied some degree of correlation over time, and a steep slope implied a higher degree of correlation than a shallow slope (Gardner 1992).

3 Nonlinear analysis

The brain may be considered as a dissipative dynamic system. A dynamic n th-order system is defined by a set of n first-order differential equations. The states of the system can be represented by points in n -dimensional space, where the coordinates are simply the values of the state variables $x_1, x_2, x_3, \dots, x_n$. The phase space is the set of all possible states that can be reached by the system. In general, a phase space is identified with a topological manifold. The sequence of such states over the time scale defines a curve in the phase space called a trajectory. In dissipative systems, as time increases, the trajectories converge to a low-dimensional indecomposable subset called an attractor (Eckmann and Ruelle 1985).

In experiments, one cannot always measure all the components of the vector giving the state of the system. Therefore, we have to reconstruct brain dynamics from a one-dimensional EEG by using delay coordinates and embedding theorem. Takens showed that an attractor, which is topologically equivalent to the original data set, can be reconstructed from a dynamic system of n variables $x_1, x_2, x_3, \dots, x_n$ by using the so-called delay coordinates $y(t) = [x_j(t), x_j(t+T), \dots, x_j(t+(d-1)T)]$ from a single time series x_j and by performing an embedding procedure, where d is the embedding dimension. The purpose of time-delay embedding is to unfold the projection back to a multivariate state space that is a representation of the original system (Takens 1981; Eckmann and Ruelle 1985).

Attractors of dynamic systems can be characterized by their correlation dimensions. The correlation dimension D_2 is a metric property of the attractor that estimates the degree of freedom of the EEG signal in our study. It determines the number of independent variables which are necessary to describe the dynamics of the central nervous system. In other words, it is a measure of complexity. While periodic and quasiperiodic systems have integer dimensions, systems of deterministic chaos have noninteger dimensions (fractals). In the latter case, the attractor is called a strange attractor. Strange at-

tractors are identified with deterministic chaos, which means that the different states of the system, that are initially arbitrarily close, will become macroscopically separated after sufficiently long times (Fell et al. 1993).

Lyapunov exponents estimate the mean exponential divergence or convergence of nearby trajectories of the attractor. Lyapunov exponents are usually ordered in a descending fashion from L_1 (the highest value) to L_n (the lowest value). Here, n is equal to the topological dimension of the phase space. At least one Lyapunov exponent is zero for each attractor (except that of a fixed point). It is the one corresponding to the forward direction of the flow. For dissipative dynamic systems, the sum of all Lyapunov exponents is less than zero. A system possessing at least one positive Lyapunov exponent is chaotic. This fact reflects the sensitive dependence on the initial conditions (Fell et al. 1993).

We applied a reconstruction procedure to each EEG segment. For the time delay T , we used the first local minimum of the average mutual information between the set of measurements $v(t)$ and $v(t + T)$. Mutual information measures the general dependence of two variables. Therefore, it provides a better criterion for the choice of T than the autocorrelation function, which only measures the linear dependence (Fraser and Swinney 1986).

Classical algorithms for calculating the nonlinear invariant measures, such as the correlation dimension and the largest Lyapunov exponent for time signals, require a very large number of computations. We calculate a nonlinear invariant measure by increasing the embedding dimension until the value of the invariant measure is saturated. The value is independent of the embedding dimension d for $d \geq d_{\min}$ (i.e., after the geometry is unfolded), where d_{\min} is the minimum embedding dimension. However, working in a dimension larger than the minimum embedding dimension leads to excessive computation. It also enhances the problem of contamination by roundoff or instrumental error because such noise will populate and dominate the additional $d - d_{\min}$ dimensions of the embedding space in which no dynamics is operating. In our new algorithm, we calculate

the D_2 and the L_1 in the minimum embedding dimension.

We determined the minimum embedding dimension by using the calculation method, presented by Kennel et al. (1992), which is based on the idea that in the passage from dimension d to dimension $d + 1$, one can differentiate between points on the orbit that are ‘true’ neighbors and those on the orbit that are ‘false’ neighbors. A false neighbor is a point in the data set that is a neighbor solely because we are viewing the orbit (the attractor) in too small an embedding space ($d < d_{\min}$). When we have achieved a large enough embedding space ($d \geq d_{\min}$), all neighbors of every orbit point in the multivariate phase space will be true neighbors. We define the embedding rate as the ratio of the true neighbors to the neighbors in the embedding dimension. Figure 2 shows a typical example of the embedding rate as a function of the embedding dimension for 16 384 EEG data points in a patient with Alzheimer’s disease. The proper minimum embedding dimension was selected as 11 in this case. Next, we can estimate the invariant measures by calculating them only in the minimum embedding dimension, which is different from the conventional method (Grassberger and Procaccia 1983). Figure 3 shows a comparison of the new method for calculating D_2 with the old. Both estimate the D_2 of the EEG at T_4 in a patient with Alzheimer’s disease. The calculation of D_2 is done once in the determined minimum embedding dimension with our new method, whereas the older methods require several calculations of D_2 at different embedding dimensions. This shows the increased efficiency and accuracy of the new method relative to the old one.

We evaluate the correlation dimension D_2 of the attractors from the EEG by using the GPA (Grassberger and Procaccia 1983). In order to calculate D_2 , one computes the correlation integral function

$$C(r) = \frac{1}{N^2} \sum_{\substack{i,j=1 \\ i \neq j}}^N \theta(r - |\mathbf{x}_i - \mathbf{x}_j|) \quad (1)$$

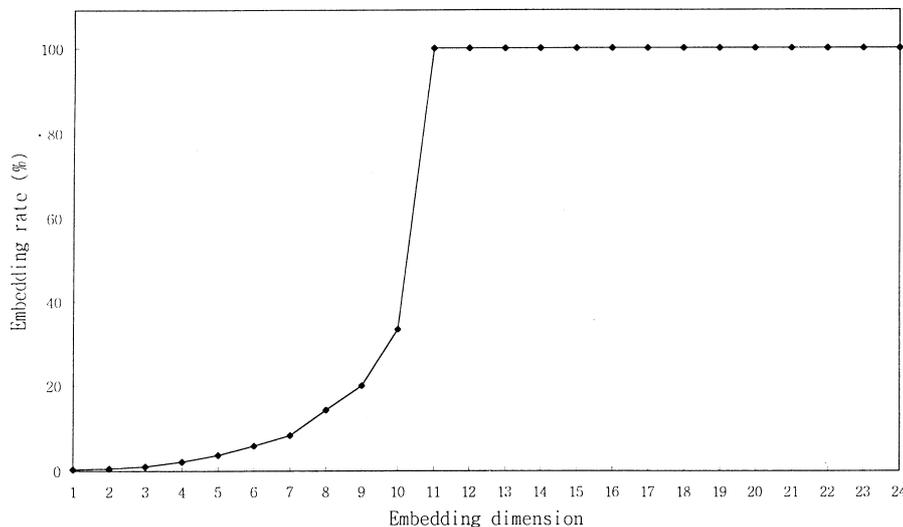


Fig. 2. Embedding rates with increasing embedding dimension for 8000 electroencephalography (EEG) data points at T_6 for the rest state. The proper minimum embedding dimension was selected as 11 in this case to calculate the invariant measures

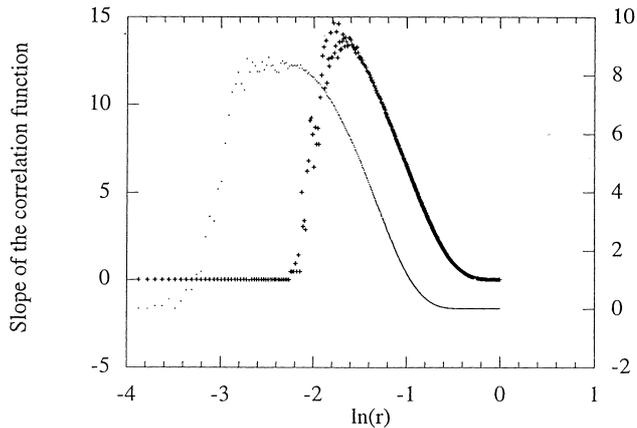


Fig. 3. Comparison of the two slope estimates derived from 16 384 EEG data points. *Dotted line:* slopes corresponding to a minimum embedding dimension of 11 derived from 16 384 EEG data points for a resting state using Grassberger-Procaccia-Algorithm (GPA) with Dvořák and Theiler's correction. *Cross symbol line:* slopes corresponding to a higher embedding dimension of 32 derived from the same data using the classical GPA. The former has a larger scaling region, which is evidence of a reliable estimate

where θ is the Heaviside function, $\theta(x) = 0$ if $x < 0$, and $\theta(x) = 1$ if $x > 0$. $C(r)$ measures the spatial correlation of the points on the attractor obtained from the time series data. For small r , it is known that $C(r)$ behaves according to a power law:

$$C(r) \propto r^{D_2} \quad (2)$$

The value of D_2 for the attractor is, therefore, given by the slope of the $\log C(r)$ versus $\log r$ curve:

$$D_2 = \frac{d \log C(r)}{d \log r} \quad (3)$$

The graph of $\log C(r)$ versus $\log r$ has a linear region called the scaling region. The GPA assumes that most of the information about the dimension is contained in the scaling region (Babloyantz and Salazar 1985).

A finite sequence of EEG data exhibits an anomalous structure in the correlation integral by overcontributing early terms from the start in the correlation integral. Realistic values for the average additive noise levels can be extracted from the curves of the correlation integral which are used to calculate D_2 . Intermediate knees in the correlation integral are related to noise contamination. The value of r for which the knee starts to appear can be used as an estimate of the noise scale. The criteria to establish the maximum scale are derived from the upper boundary of the scaling region in the correlation function (Principe and Lo 1991). We use a slight modification of the GPA proposed by Theiler (1986), to prevent the anomalous structure in the correlation integral:

$$C(r, N, M) = \frac{2}{N^2} \sum_{n=W}^N \sum_{i=1}^{N-n} \theta(r - |\mathbf{x}_{i+n} - \mathbf{x}_i|) \quad (4)$$

In our study, W is determined by the first local minimum of the mutual information, i.e., by the delay time T .

When we analyze real data, the scaling region is very often observed to oscillate around some straight line. These oscillations may be either intrinsic sample oscillations caused by the lacunarity of the attractor or finite sample oscillations caused by the limited amount of data (the edge effect). We analyzed a modification of the GPA proposed by Dvořák and Klaschka (1990), to compensate for the edge effect.

We calculate the largest Lyapunov exponent L_1 by applying a modified version of the Wolf algorithm (Wolf et al. 1985) and by following a proposal by Frank et al. (1990). Essentially, the Wolf algorithm computes the initial vector distance d_i of two nearby points and evolves its length at a certain propagation time. If the vector length d_f between the two points becomes too large, a new reference point is chosen with properties minimizing the replacement length and the orientation change. Now, the two points are evolved again and so on. After m propagation steps, L_1 results from the sum of the logarithm of the ratios of the vector distances divided by the total evolving time:

$$L_1 = \frac{1}{m} \sum_{i=1}^m \frac{\ln \frac{d_f}{d_i}}{\text{EVOLV} \cdot dt \cdot \ln 2} \text{ (bits/s)} \quad (5)$$

where dt , d_i , and d_f are the sampling interval and the initial and the final separations between the points in the fiducial trajectory and in the nearest-neighbor trajectory separated in time by i th EVOLV step, respectively (Wolf et al. 1985).

By using the weight function proposed by Frank et al. (1990), we improve the L_1 estimate by widening the search to allow replacements to be well-aligned points lying further apart but still within the region of linear dynamics:

$$W(r, \theta) = \left(\alpha + \beta \left(\frac{b-r}{b-a} \right)^r \right) \cdot \cos \theta \quad (6)$$

where b and a are distances over which the dynamics is assumed to be linear and to be noise-dominated, respectively, r is the radial separation between the candidate and the evolved benchmarks, and θ is the angular separation between the evolved displacement and the candidate replacement vectors. The numeric parameters α , β , and γ control the relative importance of the proximity to the alignment priority.

As suggested by Principe and Lo (1991), we use the information contained in the power spectrum of the signal segment for the proper evolving time EVOLV. We select the $1/e$ spectral frequency – the frequency that divides the power spectrum in the ratio of $1/e$ – as the frequency to be used to obtain the number of points for the EVOLV step.

4 Experiments

The experiment consisted of three blocks. Each block contained three trials which lasted for 30 s. Trials were separated from one another by an interval of 1 min.

Nine distinct computer-generated musical sequences were played through a computer speaker, recorded on an analogue tape, and replayed from the tape recorder. The sequences of music were identical for all subjects.

During block 1, both the pitch (melody) and the duration (rhythm) of the music was varied. The variations of the pitch and the duration of the musical stimuli had $1/f$, white, and brown distributions; the first trial contained a $1/f$ melody and a $1/f$ rhythm, the second a white melody and a white rhythm, and the third a brown melody and a brown rhythm.

During block 2, only the pitch of the musical stimuli was varied, with the duration being kept constant (250 ms). During block 3, only the duration was varied, with the tone frequency being kept constant (440 Hz). These variations also had $1/f$ white, and brown distributions. The nine distinct music inputs of the various patterns are summarized below.

The experiments were conducted in a dimly illuminated, soundproof room. The EEGs were recorded from ten healthy subjects, five men and five women, aged between 7 and 26 years (mean age 20.3 years). All subjects were informed verbally about all aspects of the experimental procedure and then asked to sign an informed consent form according to the Helsinki convention on human studies. No subject was taking any medication. At the beginning of the experiment, the subjects were given earphones to listen to the musical stimuli and were instructed to relax in a comfortable reclining chair with eyes closed; electrodes were attached to their heads. They were told not to move any part of their bodies during the recording of the EEG.

The EEGs were recorded from 6 channels using Ag/AgCl electrodes according to the international 10–20 system. The electrical impedance was 5 kOhms for all electrodes. To study the limbic system, which is thought to be responsible for our emotions, the electrodes were placed concentrically at the following areas: frontal lobes 7 and 8 and temporal lobes 3, 4, 5, and 6 (F_7 , F_8 , T_3 , T_4 , T_5 , T_6) against ‘linked earlobes’. The data were amplified by a Nihon Kohden EEG-4421K using a time constant of 0.1 s and a high-frequency cut-off of 35 Hz. The data were digitized using an IBM personal computer (PC). The sampling frequency was 400 Hz for all trials. For comparison, data were collected for 30 s without any sound; this was the ‘rest state’.

Twenty seconds of EEG data (only 8000 data points) were selected for the computation because most subjects commented that they could concentrate on each stimulus for about 20 s. After experiment, the subjects had to record informally their subjective ratings regarding their interest elicited by the musical stimuli.

The differences of the nonlinear measures between groups were analyzed using analysis of variance (ANOVA) and subsequent t -test.

5 Results

First, we constructed phase spaces using the delay coordinates proposed by Takens. We used the time

delays estimated by the method of mutual information to reconstruct the attractor. The time delay, T , in each case was about 25–30 ms, which was determined from the first local minimum of the mutual information. D_{2s} were calculated by a slightly modified version of the GPA. Embedding of 11–18 were used for all subjects. The slope of the correlation integral curve in the scaling region was estimated by a least-squares fitting method (Fig. 3).

All the subjects gave ratings of interest right after the experiment. They all agreed that the musical stimulus with both a $1/f$ melody and a $1/f$ rhythm was more pleasing than the other music. This confirms that the pleasure from music is partly related to the $1/f$ spectral density.

In all the experiments, the nonlinear invariant measures had nonuniform distributions all over the head. For the block 1 experiments, D_{2s} with their standard deviations were calculated in all channels for the $1/f$, white, and brown music (melody and rhythm) and for the rest state. The subjects had lower values of D_2 at the T_6 channel (a right temporal electrode) when they were listening to $1/f$ music, as shown in Fig. 4 (F tests,

Table 1. Distinct music inputs of various patterns

Melody variations	Rhythm variations
Block 1	
$1/f$	$1/f$
White	White
Brown	Brown
Block 2	
$1/f$	Constant
White	Constant
Brown	Constant
Block 3	
Constant	$1/f$
Constant	White
Constant	Brown

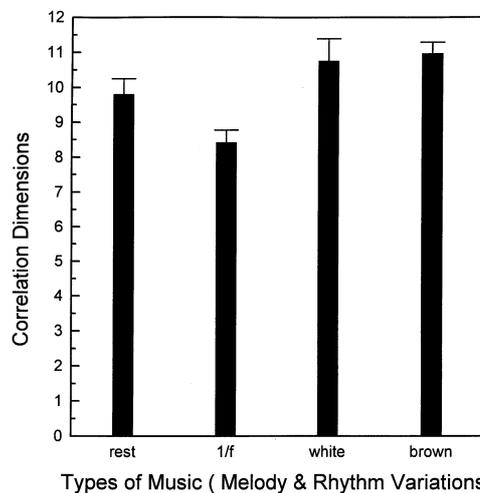


Fig. 4. Mean values of D_{2s} for 10 subjects, with standard deviations, derived from time series of EEGs at T_6 for the rest state and various music states (block 1)

$F(3, 36) = 6.78; P < 0.01$). The differences in D_2 s between $1/f$ music and white or brown music were about 1.0–1.5 units, with the white and brown music inducing somewhat higher D_2 s than that electrode. D_2 for $1/f$ music is significantly lower than that for white music (pairwise t -test, $P < 0.01$), for brown music ($P < 0.01$) and for the rest state ($P < 0.01$). The differences of D_2 between the rest state and white music and brown music are also statistically significant (white music, $P < 0.05$; brown music, $P < 0.01$). However, D_2 for white music at the T_6 channel is not statistically different from that for brown music ($P > 0.05$). Other channels showed no significant differences between the different musical stimuli ($P > 0.05$). Since all the subjects reported that $1/f$ was the most pleasing music among the different stimuli, we can infer from this result that the emotional state of musical pleasure corresponds to a lower dimension of the attractor.

The other nonlinear invariant measure, the largest Lyapunov exponent L_1 , was calculated for all subjects in all channels. The evolving time, $EVOLV$, was selected as the $1/e$ spectral frequency and was about 200 ms. The calculation of L_1 naturally depended on the time over which the trajectory was evaluated. After 200 propagation steps, the values converged in an interval of ca.0.9% around the final value of L_1 .

The average values of the L_1 s and their standard deviations at the T_6 channel for various musical states (melody and rhythm variations) and the rest state are shown in Fig. 5. The average values at that channel are lower for the $1/f$ music state than for the other states ($F(3, 36) = 5.61; P < 0.01$). The differences of L_1 between $1/f$ music and white and brown music states at the T_6 channel are very significant, about 1.0–1.5 bits/s. L_1 for $1/f$ music is significantly lower than that for white music ($P < 0.01$), for brown music ($P < 0.01$) and for the rest state ($P < 0.01$). The differences of L_1 between the rest state and white and brown music are also statistically significant (white music, $P < 0.05$; brown mu-

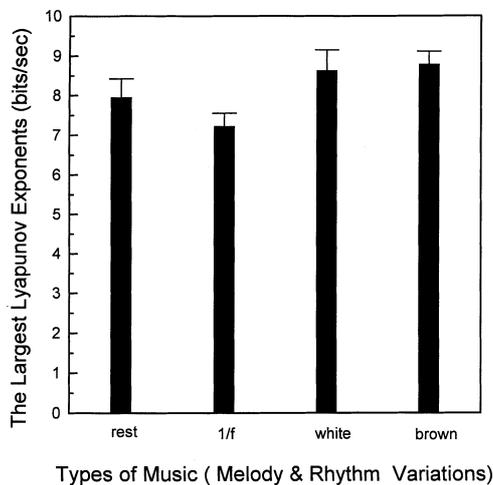


Fig. 5. Mean values of L_1 s for 10 subjects, with standard deviations, derived from time series of EEGs at T_6 for the rest state and various music states (block 1)

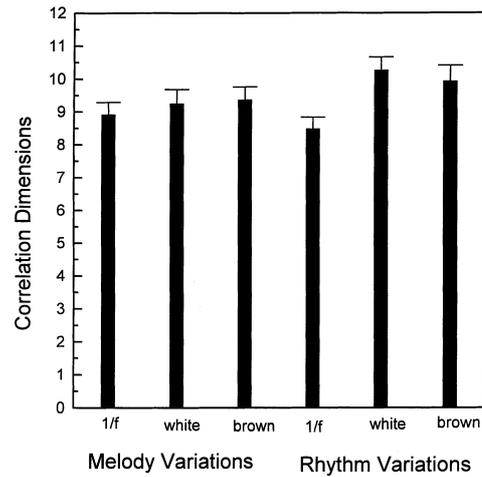


Fig. 6. Comparison of mean values of D_2 s for 10 subjects, with standard deviations, derived from time series of EEGs at T_6 for melody variations and for rhythm variations (block 2 vs 3)

sic, $P < 0.05$). However, L_1 for white music is not statistically different from that for brown music ($P > 0.05$) like D_2 . Other channels showed no significant differences between the different musical stimuli. The result for L_1 is very consistent with that for D_2 . This implies that the emotional state of musical pleasure corresponds to a less chaotic attractor.

Figures 6 and 7 show the average values of D_2 s and L_1 , with their standard deviations, at the T_6 channel for the EEGs in blocks 2 and 3. We can see that the subjects had a reduced D_2 and L_1 if the melody or rhythm was $1/f$. In the case of D_2 , $F(2, 27) = 3.39 (P < 0.05)$ for melody variations, and $F(2, 27) = 5.63 (P < 0.01)$ for rhythm variations. For melody variations, D_2 for $1/f$ music is significantly lower than that for white ($P < 0.05$) and brown ($P < 0.05$) music. However, D_2 for white music is not different from that for brown music ($P > 0.05$). For rhythm variations, D_2 for $1/f$ music is also significantly lower than that for white

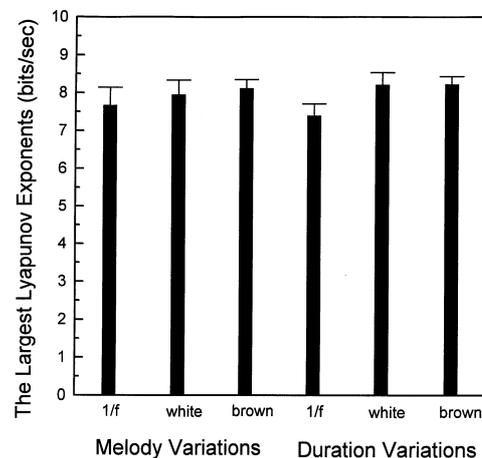


Fig. 7. Comparison of mean values of L_1 s for 10 subjects, with standard deviations, derived from time series of EEGs at T_6 for melody variations and for rhythm variations (block 2 vs 3)

($P < 0.01$) and brown ($P < 0.01$) music. D_2 for white music is not different from that for brown music ($P > 0.05$).

For L1, $F(2, 27) = 3.36$ ($P < 0.05$) for melody variations and $F(2, 27) = 5.51$ ($P < 0.01$) for rhythm variations. For melody variations, L1 for $1/f$ music is significantly lower than that for white ($P < 0.05$) and brown ($P < 0.05$) music. However, L1 for white music is not different from that for brown music ($P > 0.05$). For rhythm variations, L1 for $1/f$ music is also significantly lower than that for white ($P < 0.01$) and brown ($P < 0.01$) music. However, the differences of L1 between white music and brown music is not significant ($P > 0.05$).

In particular, the changes in the measures were more distinct for rhythm than for melody variations. By comparing the results for block 2 with block 3, we can see that the variation of the rhythm contributes more to the pleasing response to musical stimuli than the variation of the melody does.

6 Discussion

The reason interesting music has $1/f$ spectra for its pitch and its duration is partially answered by the 'theory of aesthetic value' propounded by the American mathematician Birkhoff. Birkhoff's theory states that for a work of art to be pleasing and interesting, it should be neither too regular and predictable nor too irregular and unpredictable (Birkhoff 1933; Schroeder 1991). Music is aesthetically interesting if it has a balanced mixture between recognition and surprise, i.e., order and complexity. One interpretation of this is that the power spectrum of the function should behave neither like boring brown music, with a frequency dependence of $1/f^2$, nor like unpredictable white music, with a frequency dependence of $1/f^0$. From our experimental results, we can assume that people tend to guess the pattern of successive notes either consciously or unconsciously while listening to music. They enjoy music with both recognition and surprise. Hence, they will soon hate or be bored with the music if it is too hard or too easy to predict the next note.

To understand in more detail the brain dynamics during music perception, we calculated two nonlinear invariant measures after dividing the EEG data into two consecutive segments (each with 4000 data for 10 s). The first segment had higher values of D_2 and L1 than the second one did. From this result, we may infer that we try to recognize the pattern of the music when we start to listen to the music. Therefore, we have more complex and chaotic brain dynamics in the earlier segment than in the later one, which is the phase in which music is enjoyed after the music pattern has been recognized in the earlier phase.

A nonlinear analysis of the EEG detected significant differences between the brain dynamics of different emotional states. Our results confirmed that the EEG, the excitation of thousands of neurons, is a good indicator of the brain dynamics of perception.

Based on several previous reports (Freeman 1991; Birbaumer et al. 1994), the reduction of D_2 during $1/f$ music perception can be explained by cell assemblies. Cell assemblies are groups of cells with plastic synapses distributed at any possible distance across the neocortex with excitatory connections among each other (Birbaumer et al. 1994). D_2 of the human EEG reflects the number of independently active neuronal cell assemblies necessary to execute a particular task and mental activity. The lower values of D_2 for $1/f$ music means that the subjects exhibited more synchronous activities of fewer cell assemblies when listening to interesting music. This is analogous to the EEGs from the array of electrodes suddenly becoming more regular and ordered for a few cycles during perception of a familiar scent studies of animal olfactory systems (Freeman 1991). In contrast, unpredictable white music and boring brown music activate more independent cell assemblies in large cortical and subcortical regions.

The results for L1 indicate that the attractors have less chaotic dynamics during $1/f$ music perception. It is reasonable that the results of L1s all over the head should be very similar to those of D_2 . (However, this is not always correct, of course.) D_2 may indicate the neurophysiological basis of the richness of associations (Birbaumer et al. 1994). Rich associations can make the brain dynamics more chaotic, and chaos in the brain may be an important factor in changing brain dynamics, representing a tendency of cell assemblies to shift abruptly from one complex activity to another in response to small inputs.

We obtained a fruitful correlation between emotional brain states and nonlinear invariant measures at the right temporal T_6 electrode. The right temporal lobe, especially the limbic system, is thought to be responsible for the perception of complex acoustic stimuli. Previous work, however, reported high correlations at the frontal electrodes by estimating the EEG dimensions (Birbaumer et al. 1994). However, we did not measure the EEG at the frontal electrodes owing to experimental circumstances. Further experiments will be done later.

Although we detected a significant correlation between the invariant measures and the emotional states only at the right temporal lobe, we cannot assert that the right temporal lobe is the precise location in the brain of the cell assemblies responsible for music perception because the activated brain regions change their interactions continuously during music perception. Electrophysiological studies have suggested that sensory, perceptual, and cognitive functions mediating tonal information processing in music should be neurologically dissociable (Tramo et al. 1990). Additionally, the spatial resolution of the EEG is not sufficient to determine the precise locations of brain activities.

Comparing the results of block 2 with those of block 3, we can see that the subjects responded more to the rhythm variations than to melody ones. This may be due somewhat to the fact that Korean popular music traditionally has a much strong emphasis on rhythms. Additionally, we analyzed the EEG data with the linear method of power spectra. All the magnitudes in the

frequency ranges of the δ (1–5 Hz), θ (5–8 Hz), α (8–13 Hz), and β (13–30 Hz) waves were added up in order to see if any frequency range could be related to a particular emotional state. However, no correlation was found, and the deviation was too small to treat the sum of magnitudes as an important parameter.

In our study, we suggested the possibility of using nonlinear analysis to quantify emotion during music perception. This approach gives us an insight into understanding the mechanism of emotional changes in the brain with a view to chaos. A nonlinear analysis provides a promising tool for detecting relative changes of emotion during the perception of music; D_2 and L_1 of the chaotic attractor of the EEG at the right temporal lobe in the human brain decrease as the pleasure from the music increases. Based on nonlinear analysis, rhythm variations contribute more to the pleasing response to music than melody variations do. This result may provide a fruitful clue to understanding the dynamical mechanism of music perception and the modeling of music perception.

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