Perception of Music and Dimensional Complexity of Brain Activity

N. Birbaumer[1,2], W. Lutzenberger[1], H. Rau[1], G. Mayer-Kress[3], I. Choi[4], C. Braun[1]

[1] Institute of Medical Psychology and Behavioral Neuroscience, Eberhard-Karls University of Tübingen, Germany. Gartenstraße 29, D 72074 Tübingen, Germany

[2] Dipartimento di Psicologia Generale, University of Padova, Italy

[3] Center for Complex Systems Research, Beckman Institute, Dept. of Physics, UIUC, gmk@pegasos.ccsr.uiuc.edu

[4] Virtual Environment Group, NCSA, Beckman Institute, UIUC

Abstract

The non-linear resonance hypothesis of music perception was tested in an experiment comparing a group of musically sophisticated and a group of less sophisticated subjects. The prediction that weakly chaotic music entrains less complex brain wave (EEG) oscillations at the prefrontal cortex was confirmed by using a correlational dimension algorithm. Strongly chaotic (stochastic) and periodic music both stimulated higher brain wave complexity. More sophisticated subjects who prefer classical music showed higher EEG dimensions while less sophisticated subjects responded with a drop in brain wave complexity to rhythmical weakly chaotic music. Subjects ratings of perceived complexity of the musical pieces followed mathematical (objective) structure of the music and did not reflect the changes in brain wave complexity. The results are interpreted in the context of an associated (Hebbian) network theory of non-linear brain dynamics.

1. Introduction

Attempts to localize musical abilities in particular brain regions were largely unsuccessful (see Sergent, 1993 for a review on positron emission tomography - PET -, and Petsche et al., 1988 on the electroencephalogram - EEG -). One result, however, emerged reliably from all observations, whether brain activity [Sergent, 1993] or endocrinological parameters [Hassler & Birbaumer, 1988] were used: musical experts or musically talented subjects are different. The nature of the difference remained obscure. Some studies found differences in hemispheric specialization between musicians and non-musicians (see Deutsch & Deutsch for a review). Neuroendocrinological measurements revealed a specific pattern of sexual hormones, the androgens (increased testosterone in females, decreased in males) in composers and highly talented adolescents [Hassler & Birbaumer, 1988].

With the exception of the EEG studies [Petsche et al., 1988], most variables used one single <u>static</u> measure, such as level of hormones, PET recordings during one particular activity or averaged event-related brain potentials during anticipation of simple musical stimuli. The generation and processing (composition and execution) of music, however, particular classical music, evolves dynamically as the piece is created, listened to or planned and executed. The activated brain regions change their interactions continuously and respond to the ongoing dynamics of the musical stimuli.

In order to describe the complex dynamics of music in the human brain (and music seems to be one of the rare exclusively human cognitive skills) we adhere to a Hebbian theoretical framework of the neuronal basis of music perception and production [Hebb 1949, Pulvermüller et al. 1994]. Each stage of music processing, beginning with the perceptual feature analysis of clef, key signature, metrum, tempo etc. continuing to the representation of pitch, duration, rhythm in memory and anticipation, planning and understanding the underlying musical structure is represented in specific assemblies of cortical cells. Cell assemblies are defined as groups of cells with plastic synapses distributed across any possible distance across the neocortex with excitatory connections among each other; the excitatory connections of a particular assembly are stronger than the background assemblies responsible for another mental activity. Assemblies are formed through contiguity: simultaneous arrival of two impulses or cascades of impulses at plastic synaptic spines strengthens their connection, and at the next occasion the input of only one or a few synapses are able to fire the postsynaptic unit [Hebb, 1949]. Since many synchronously excitatory afferents have to converge on the cortical cell before it's firing, excitation threshold is reduced in a particular assembly only for that neural activity matching the specific assembly. Cell assemblies ignite if only part of its neurons are excited. Each cell of an assembly can participate in many other assemblies, the pattern of threshold reduction determines the specificity of the assembly for a particular mental activity.

Cell assemblies are formed primarily during development but cortical reorganization through formation of new or "priming" of already established assemblies is possible at any age [Elbert et al., 1994]. A precise localization of cell assemblies in the human brain responsible for music is impossible. Music perception and production is a highly personal and unstable experience extremely variable across and within people and musical scores. Since the neuropsychological literature reports many cases of amusia without aphasia, language assemblies and music assemblies are different. This does not exclude the possibility that for particular styles of music and particular persons there is a strong overlap between language and music assemblies [Pulvermüller et al., 1994], explaining the frequent co-occurrence of some aphasic disorders with specific deficiencies in music perception [Sergent, 1993].

Several studies indicate that musical experts which process music more "deeply", show much more widespread but also more synchronous oscillations in the cortical EEG to their preferred pieces of complex

classic music [Petsche et al., 1988]. Less trained and less talented listeners prefer highly repetitive ("rhythmic") music with less variation (see Lerdahl & Jackendoff, 1983). This would support the idea that "complex" music, expressing unpredictable change in harmonic and rhythmic progression activate more independent cell assemblies in a larger extension of cortical and subcortical regions in musically educated and/or talented subjects showing a preference for the more complex music only. In contrast, subjects with a preference for less complex, repetitive music should show a more repetitive synchronous activity of <u>fewer</u> assemblies to their preferred more "simple" music with a tendency of those assemblies to become synchronized and therefore less independent. In addition, the diversity of cortical areas analyzing the musical stimuli should be decreased, only a few brain regions "swinging" in the rhythmic domain reflecting the preferred ignition of the music assemblies.

The hypothesis tested here therefore proposes a "resonance" dynamics of the individual human brain and its assemblies specialized for music perception to its preferred musical structure. Or to put it more bluntly: Complex music produces complex brain activity in complex people, simple music excites simple brain activity in simple people.

One way to define complexity in music as well as in electric or magnetic brain recording is the use of algorithms derived from non-linear dynamic ("deterministic chaos") for both the music stimuli and the resonant brain activity.

EEG and Non-Linear Dynamics

In a recent review [Elbert et al, 1994], we summarized the methodological problems and empirical results using algorithms derived from non-linear dynamics to analyze physiological responses such as EEG, MEG (magnetoencephalography), single cell spikes, heart rate etc. For the present report, only the literature on EEG-dynamics is relevant (for methodological details see Lutzenberger et al, 1992 a,b). The algorithm used allows the reconstruction of long time series such as the EEG which may be inherently aperiodic but non-stationary. The time series is embedded in a reconstructed "state space". The number of independent variables necessary to reconstruct the whole time series is called the "dimension" of the state space or the "embedding dimension" of the reconstructed time series. The geometrical structure or point where the reconstructed time-series tends to converge is called the attractor of the particular time series. The most frequently used algorithm to reconstruct an attractor from a given time series is based on delay coordinates. A common method for analyzing the dimensional complexity of the attractor (with many potential pitfalls, see e.g. Holzfuss & Mayer-Kress., 1986 and Layne et al., 1986) is the computation of the correlation dimension.

In order to test the above stated resonance hypothesis, three types of musical harmonies with different complexity and three types of rhythmic modulations were constructed, and the EEG from several brain locations in musically more or less sophisticated subjects was recorded.

2 Methods

Experimental procedure

The experiment described here was performed after another experiment of about 150 min duration in which EEG responses to different odor stimulation have been investigated. This part of the experiment lasted for about 45 minutes. The procedure was identical for each subject. At the beginning of the present experiment, subjects received a headphone for application of the acoustic stimuli. Subjects sat in a sound proof chamber on a comfortable reclining chair with EEG electrodes being attached to their head.

The presently described experiment consisted of three blocks. Each block contained 12 trials which lasted for 15 s. Trials were separated from each other by intertrial intervals randomly varying between 8 and 15 s. The random variation of the intertrial interval was introduced in order to prevent systematic EEG variations associated with expectancy and preparation. During a single trial, the acoustic stimuli were presented without any other stimulation. Subjects had to attend to these stimuli. After each trial, subjects had to perform two subjective ratings regarding (1) the subjective interest elicited by and (2) the subjective complexity of the stimuli on a 1 to 9 analogue scale with 1 indicating low interest/complexity and 9 indicating highest interest/complexity. During block 1 (mode "melody"), only the pitch of the piano sounds was varied (melodic complexity) with rhythm kept constant. Generation and features of the acoustic stimuli are described below. During block 2 (mode "rhythm"), only the rhythm of the wood-drum like sounds have been varied with tone frequency being constant. During both blocks, three different kinds of trials (four trials of each complexity condition) have been presented in pseudo randomized sequence. Complexity conditions of the stimuli varied in three groups, with the first condition consisting of periodic, the second of chaotic and the third of stochastic stimulus sequences. The third block (mode "melody & rhythm") also contained 12 trials which were separated into three conditions. In this block, variation of melody and rhythm was combined according to blocks 1 and 2. Condition 1 contained periodic melody and periodic rhythm, condition 2 periodic rhythm but stochastic melody, condition 3 stochastic rhythm and stochastic melody. The computer-synthesizer generated sequences of stimuli were recorded on an analogue tape and replayed from the tape recorder. Sequence of stimuli and intertrial intervals were identical across subjects.

Musical complexity

Acoustic stimuli were created using a Yamaha Synthesizer connected via a Studio III MIDI interface to a NeXT computer. For the generation of the MIDI signals we used the software package *Chaos.app* originally written by R. Bidlack and modified by Ed Erwin. We supplied several types of structure based upon the following criteria for producing sounds: musical and psycho acoustic considerations, acoustic design considerations.

Musical and psycho acoustic considerations: We have maintained a consistent ratio and scale between the chaotic signal that is making patterns and the auditory signals reproducing those patterns. We selected values for acoustic parameters to maintain consistent auditory variability (perceived degree of change) across diverse parameters (rhythm and pitch in this case).

Sound descriptions

Block 1 (mode "melody"):
         - Four trials with periodic sequences (period 7 -> period 5 -> period 7 -> period 5)
         - Four trials with intermittency type chaos (all four stimuli were generated in the intermittency region near period 5)
         - Four trials with quasi-random sequences (high-dimensional chaos) (all four stimuli were generated with uniformly distributed uncorrelated pseudo-random numbers, i.e.

$$\xi_{n+1} = a\,\xi_n \bmod 1, \qquad a \gg 1\,).$$

Instruments: In order to present well-differentiable pitches we have combined two pitched instrument characteristics: the onset characteristic of a piano and transient characteristic of a harpsichord. The pitch range for these examples was 3 octaves, with the fundamental frequencies of the tones falling roughly in a range of 100 Hz to 8000 Hz.

Block 2 (mode "rhythm"):
The same pattern-structure information found in the first trials was used, in the same order. The information was used to vary onset-time (rhythm) rather than pitch.

Instruments: In order to present rhythms efficiently, we decided to present the structure in percussive instruments which present timbre as a primary characteristic with pitch as a secondary characteristic. The sounds has a leather-drumhead-like sustain characteristics with a wood-drum-like onset. The values for onset intervals ranged within a factor of 4.

Block 3 (mode "melody & rhythm"):
The same pattern-structure information found in the previous trials was used, in the same order. The information was used to vary both pitch and rhythm.

Instruments: The instrument applied for Block 3 was derived from the instrument used for Block 1. To equalize the rhythm and pitch perception, a harp-like sustain and decay was incorporated into the original sound. The frequency and time ranges of the previous trial blocks were maintained.

Subjective evaluation
After the experiment and after removal of the electrodes, subjects performed a short questionnaire asking:
1) how they estimate their own musical capability
2) how many hours a week they perform music
3) how many hours a week they hear music
4) how much they like classical music
5) how much they like popular music
6) which instruments they perform
7) how they estimate their rhythmic capability
8) how they like dancing
9) how they like Jazz
10) which kind of musical education they had.

This questionnaire had the intention to evaluate the musical habits of each subject.
The range of the scale was: 1 = very low -- 5 = very high

Subjects
In this experiment we had eighteen healthy male and right handed volunteers aged between seventeen and forty-one years (mean age: 21.8 years). Prior to the experiment subjects were informed verbally about all aspects of the experimental procedure and then asked to sign an informed

consent according to the Helsinki convention on human studies. All subjects were free of any medication. Subjects were paid fifteen Deutschmarks (approximately 10 US $) per hour for their participation.

EEG-Recording

The EEG was recorded from 9 sites using Ag/AgCl electrodes according to the international 10-20 system and linked Ag/AgCl electrodes placed on the mastoids. Electrical impedance was 5 kOhms or less for all electrodes. The electrodes were placed at the following placements: F3, Fz, F4, C3, Cz, C4, P3, Pz, P4. All channels were amplified with a bandwidth from 0.016 Hz to 70 Hz and sampled at a rate of 256 Hz. Vertical eye movements were measured by two EOG-electrodes fixed one centimeter above and below the center of the right eye. Horizontal eye movements were recorded with electrodes at the outer canti of the eyes. The EEG was corrected for ocular artifacts with a regression method based upon the vertical and horizontal EOG and converted to a 128 Hz sampling rate.

Data Preparation

For each music sequence an interval of 16 s in duration was selected for the computation. Thus the length of each EEG-trace was 2048 points. The following measures were calculated for every EEG trace:

(i) The EEG alpha power was obtained from the average log power in the range from 8 to 12 Hz. The power spectrum was calculated by averaging the Fourier transforms of 15 overlapping 2 s segments (256 points.), using Parzen windows on the 2 s segments.

(ii) EEG beta power was calculated as the average log power in the range from 14 to 30 Hz.

(iii) The state space dimension of the EEG: The singular value decomposition was based on the autocovariation function with time-lags ranging from 0 to 32 points corresponding to 0.25 seconds. A symmetrical 32x32 matrix was constructed with the covariances as elements. The first row was the autocovariation function itself, in the second row, elements were shifted by one column to the right, in the third row by two columns etc. so that the diagonal element was always the covariance with time lag zero. Then the eigenvectors and eigenvalues were obtained. A subset of the eigenvectors was used to reconstruct the state space. Only eigenvectors were selected with eigenvalues larger than twice the smallest of all 32 eigenvalues. This selection was used to separate the signal from the noise. The criterion chosen seems somewhat arbitrary but has two advantages: It is independent of the particular gains used and it is easily reproducible among different laboratories. A calculation of the dimension was done separately for 32 equidistant points using the method of 'pointwise dimension' as proposed by Mandelbrot [1977] and for the first time applied to physiological time series by Mayer-Kress and Layne [1987]. Given a distinct reference point, the number of points $N(r)$ which lie in a hyper cube with radius r around this chosen point is counted. This counting is performed for subsequently larger radii until ultimately all points of the time series lie within this hyper cube. For the present computations, the different radii r_i were chosen in a data driven way. The distance between subsequent radii was selected such that each enlargement of the radius increased the total count by an exponential increasing number of points, i.e. $N(r_{i+1}) - N(r_i) = N(r_i)$, $N(r_1) = 2016/20$. This automatically reduces the problems associated with small distances. The counts are plotted against r using a double logarithmic scale. The resulting function starts with a straight line of a certain slope, but then declines parallel to the abscissa. A linear fit is performed on

the straight segment, the slope of which is used for further calculation of the dimension. In order to obtain an estimation of the straight segment, only the lowest ten values are chosen first. If the highest of these ten values has the largest distance to the straight line, the linear fit is recalculated for nine values only. If again the highest of these has the largest distance from the straight line, it is omitted from the next calculation. The process is repeated until the highest point has no more the largest distance from the estimated straight line. Typically, this procedure results in an estimate out of the five to seven lowest radii for the slope. After a slope has been determined for each of the reference points, the median determines the desired fractal dimension.

Data analysis
The experiment is arranged in a variance analytical design (see e.g. Winer, 1971).One subject was removed from all data analysis due to messy EEG recordings. Another subject had practically no musical abilities. This both were omitted from the group analysis. For the analysis of the EEG the electrodes were arranged in a 3 by 3 array and ANOVAs (ANalysis Of VAriance) were calculated with the between factors electrode rows (left, middle, right), electrode columns (frontal, central, parietal), sound complexity (periodic, chaotic, stochastic), and type of modulation. Two approaches were used: The first analysis did not differentiate between the musical background of the subjects and included all three types of modulation. A second analysis was based on the subjects preferred type of music: seven subjects preferred classical music and nine subjects preferred popular music. We expected a differential responsiveness of these groups to the type of modulation. For this approach we only used the two pure types of modulation (mode melody and mode rhythm). For all ANOVA′s Greenhouse-Geisser epsilon values were applied to correct for the lack of sphericities in the covariance matrices.

3. Results

Global Analysis of Dimensional Complexity
The analysis of the EEG dimension showed significant effects of electrode rows ($F(2,30) = 9.8$, $\varepsilon = 0.89$, $p < 0.001$) and of electrode columns ($F(2,30) = 4.5$, $\varepsilon = 0.91$, $p < 0.05$) which demonstrate a non- uniform distribution over the head. With respect to the experimental variation, we found a significant interaction of electrode rows and complexity ($F(4,60) = 7.1$, $\varepsilon = 0.66$, $p < 0.002$). This effect is illustrated in Figure 1: the low dimensional chaotic music induced a reduction of the dimension mainly in the frontal electrodes compared to the periodic and the stochastic music, which showed no significant differences. The parietal electrodes showed no significant effects of complexity while the central electrodes showed moderate effects similar to the frontal electrodes. These effects were confirmed by post-hoc t-tests. No effects of the type of modulation were found.
The number of principal components used for the calculation of the dimensions was on the mean 12.2 (sd 0.3) which covered on the mean 82.5 % (sd 2.3 %) of the variance. These measures did not exhibit any significant effects for the groups of stimuli and modulation modes. The explained variance was smallest in the lateral frontal region and largest in the central region ($p < 0.01$). EEG alpha showed the well known topographical distribution with much more power in the parietal region than in the frontal and central region ($F(2,30) = 34.4$, $\varepsilon = 0.70$, $p < 0.001$) but no significant experimental variations. EEG beta was increased during rhythm modulation as compared to the

melody modulation and the combined modulation (F(2,30) = 5.9, ε = 0.68, p <0.025).
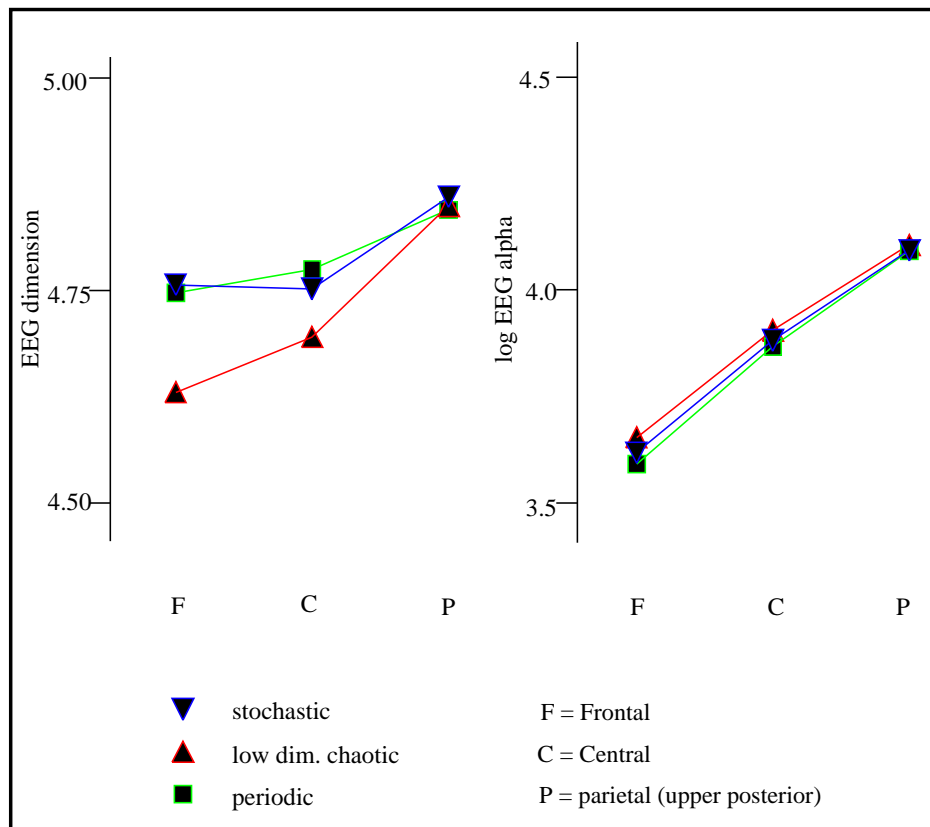

Figure 1:
Measures of EEG dimensions and EEG alpha at different locations on the scalp, separated for the three different conditions.

Partition According to Hearing Preferences
The analysis with the group factor music preference (classical vs. popular music) and the restriction to the two pure types of modulation (melody vs. rhythm) confirmed the above interaction of electrode rows and complexity (F(4,56) = 5.7, ε = 0.51, p <0.008). In addition, we found a significant interaction of groups, complexity, and type of modulation (F(2,28) = 5.1, ε = 0.98, p <0.02) which is illustrated in Figure 2. Subjects preferring classical music responded with a reduction of the EEG dimension if the melody modulation was chaotic while subjects preferring popular music showed this effect when the rhythm was modulated.
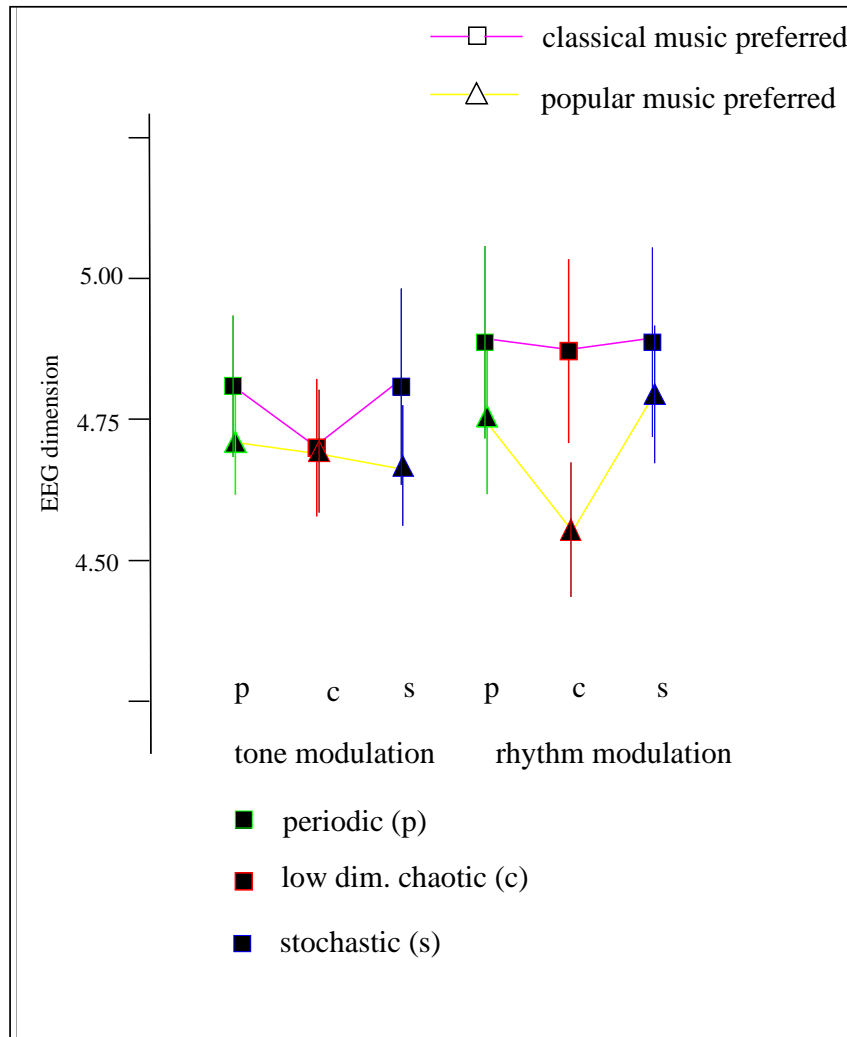
Figure 2: Variation of task dependent EEG dimensions, separated for the music preference groups.

EEG alpha and beta power revealed no additional effects.

For the complexity rating which was performed immediately after each trial, the 2 (group: classical vs. popular music preferred) by 3 (complexity condition: periodic, chaotic, stochastic) by 2 (mode: melody vs. rhythm) ANOVA showed a significant effect of complexity ($F(2,28)=31.3$; $p<.001$), a significant effect of mode ($F(1,14)=21.0$; $p<.001$), and a significant interaction of complexity and mode ($F(2,28)=13.4$; $p<.001$). These results are shown in Figure 3. Especially for the melody mode, the subjective complexity rating followed the mathematical complexity of the stimuli. Interestingly, both groups of subjects showed no significant difference in this relationship. For the rhythm mode, this relation was less clear: Subjects preferring classical music reported highest complexity for the chaotic rhythm. Consequently, it can be argued that the manipulation of the independent variable "complexity" of the stimuli led to a subjective perception following the experimental manipulation.
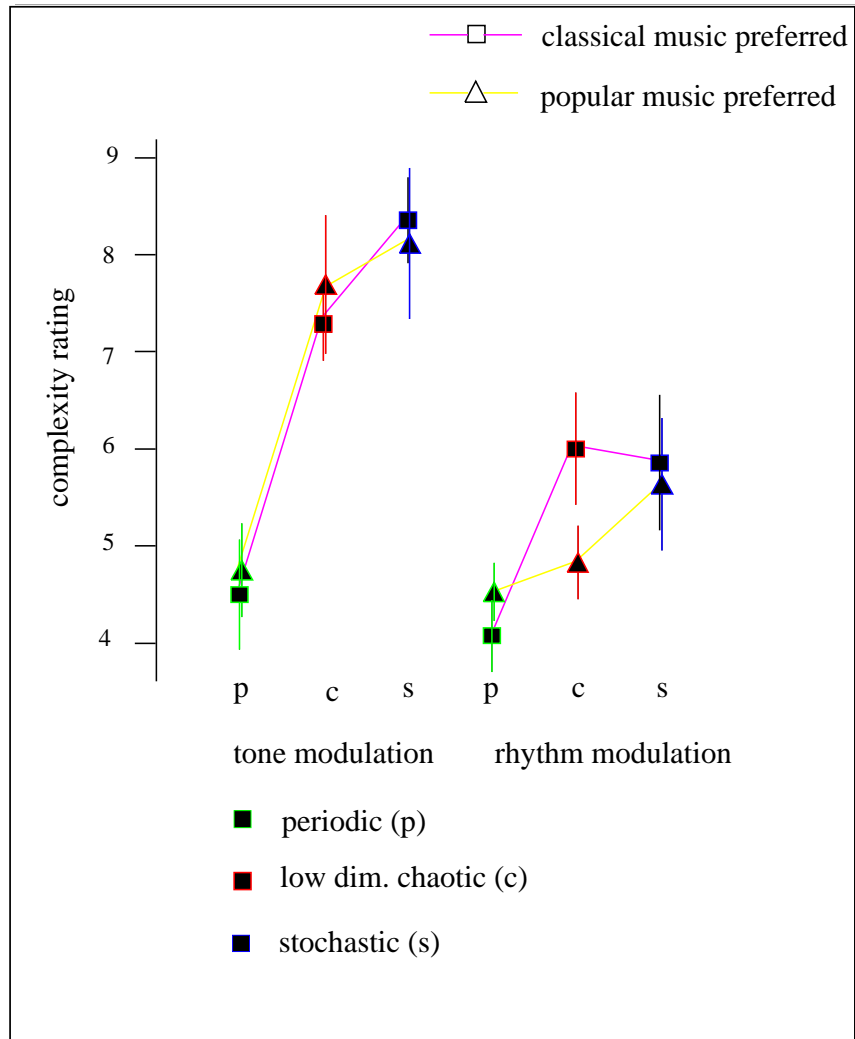
Figure 3: Variation of task dependent subjective complexity ratings, separated for the music preference groups.

The interest rating, which also was performed immediately after each trial, was sensitive to the complexity manipulation $(F_{(2,28)}=14.0; p<.001)$ with the relationship being linear for the melody mode but not linear for the rhythm mode (interaction complexity condition x mode: $F_{(2,28)}=9.6; p<.01$). The stochastic melody was rated as being most interesting, the chaotic melody as medium interesting and the periodic melody as least interesting. The chaotic rhythm, however, was rated as most interesting, followed by the stochastic rhythm with the periodic rhythm being rated as least interesting (Figure 4).
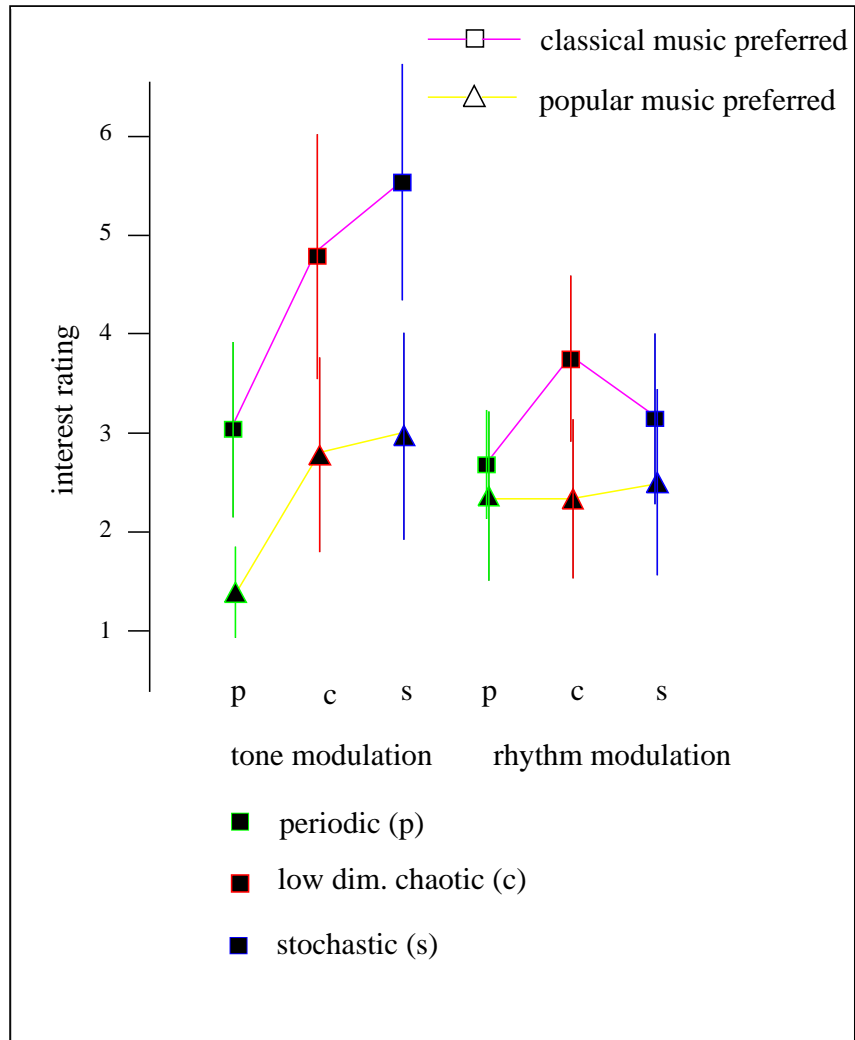
Figure 4: Variation of task dependent interest ratings, separated for the music preference groups.

4. Discussion

The hypothesis that we perceive something as aesthetically interesting if we have a balanced mixture between recognition and surprise has, to our knowledge, first been formulated by the mathematician and dynamical systems theorist George David Birkhoff (1884-1944) [Birkhoff, 1933]. Birkhoff defined the "aesthetic" measure (M) or "feeling of value" as the ratio of order (O) to complexity (C). In view of the inherent difficulty of defining O or C empirically, he proposed a definition of "aesthetic feeling" which closely resembles the idea behind the experiment reported here: " ... it must be the associations rather than the sensations themselves, which are to be regarded as thee determining factor with aesthetic experience" "... association by contiguity operate to connect any pure tone with its overtone" (p. 323).

Previous work of our group [Elbert et al., 1994, Lutzenberger et al., 1992 a,b, Schupp et al., 1994] has indicated that the correlational dimension of the human EEG reflects the number of independently active neuronal cell assemblies necessary to execute a particular task or mental challenge. In a more colloquial expression, EEG dimensions may indicate the neurophysiological

basis of "richness of associations".

For the discrimination among the complexity of different observed EEG signals we computed a dimensional complexity parameter with algorithms introduced by Lutzenberger et al. [1992a,b]. We emphasize the relative variation of this parameter and not its absolute value, which has been shown to be quite problematic (see e.g. Holzfuss & Mayer-Kress, 1986). We observe that low-dimensional, chaotic sequences produce a significant reduction in dimensional complexity compared to both periodic as well as stochastic sequences. This happens particularly in the prefrontal regions. It is also in agreement with Birkhoff's principle that this resonance phenomenon happens for the melodic sequences for both groups whereas it is only observed in the "popular music" group in the case of the rhythmic sequences. Popular music has a much stronger emphasis on rhythmic structures than the European classical music.

The type of chaos that we have chosen for this experiment is known as "Intermittency"; its dynamical characteristic of intermittent signals alternates between times in which we perceive a regular (periodic) pattern and irregular, chaotic bursts which occur at unpredictable time intervals. In a very loose way we can compare this structure with the alternation of *theme* and *improvisation* in Jazz music (See e.g. Mayer-Kress et al. 1994a). In this work we did not experiment with the third category of musical perception, the perception of sound-quality, or the *timbre* of the sound. The sounds that we presented were all of a well recognizable nature. It might be interesting to investigate the possibilities of similar resonance phenomena in the perception of sounds of constant rhythm and pitch but with a variable complexity of the timbre. Attractors from ordinary differential equations such as the Chua oscillator [Mayer-Kress et al, 1993, 1994] might be especially suitable for generating sounds with a wide variety of timbre-complexity.

Subjective interest may at least in part be determined by subjectively experienced complexity, whose neurophysiological equivalent can be only in part derived from the EEG complexity measure. Subjective interest, particularly in the musically sophisticated subjects, is reflecting the richness or diversity of associative connections evoked by a particular piece of music. Diversity of associative connections is exactly what the correlation dimension measure depicts. The high dimensional EEG complexity of periodic but subjectively complex and interesting music can therefore be seen as an additional argument for the above stated interpretation.

The fundamental difference in brain response of musically sophisticated and less trained subjects was confirmed, adding to the already available literature [Petsche et al., 1988] which reliably finds physiological and psychological divisions of the two types of subjects. Our data for the first time may point toward the psychophysiological nature of this difference. Sergent [1993], in her admirable review on the musicians brain already remarked that impoverished music is reduced to rhythmic modulations with few unexpected, less chaotic progression. The majority of less educated listeners prefer those rhythmical modulations which obviously "pull" their brain activity in a less complex periodic oscillatory response shutting off all competing assemblies. We found a similar response pattern in intelligent and less intelligent subjects [Lutzenberger et al., 1992 a]: During rest, intelligent subjects create increased frontal dimensional complexity while the dulls brain "drops" into a much simpler frontal attractor. Again, the common physiological basis of both phenomena is the number of simultaneously active but non-overlapping cell assemblies. Overlapping cell assemblies are synchronized in a harmonic or an identical brain rhythm of the externally presented rhythm and hence reduce the number of state-space dimensions which create the dynamics of the given

assemblies. Since there is a high correlation between musical talent and intelligence [Hassler & Birbaumer, 1988], both results resemble each other. The preference for complex music in intelligent groups reflect their brains increased associative diversity with a high number of independent assemblies and therefore music memories.

The difference between the three types of music (high and weakly chaotic and periodic) is confined to frontal brain regions. The same result was found for variations in intelligence [Lutzenberger et al., 1992 a] differences between mental imagery and perception of diverse objects [Schupp et al., 1994]. The more intelligent subjects showed increased dimensional complexity in prefrontal regions. Also creativity (measured by standardized psychometric tests) covaries with frontally augmented EEG-dimensions. Apart from the general explanation that processing of music seems to be an exclusive human trait appearing as late in the phylogenetic and ontogenetic evolution as the prefrontal cortex, all the mentioned mental processes (listening to music, creative thinking, imagery) involve delay of immediate reinforced behavior and active working memory. Both cognitive functions are more or less exclusively frontally located [Goldman-Rakic and Friedman, 1991]. It is therefore not surprising that realization of the "highest"(latest evolutionary) cognitive skills used the participation of additional frontal cell-assemblies which is expressed in an increased frontal dimensional EEG-complexity.

References

Birkhoff, G.D. [1933] 'Aesthetic measure', Cambridge, Mass., Harvard, University Press.

Goldman-Rakic, P. & Friedman, H.R. [1991] The circuitry of working memory revealed by anatomy and metabolic imaging, in: Levin, H.S., Eisenberg, H.M. & Benton, A. (eds.) Frontal lobe function and dysfunction. Oxford University Press, Oxford.

Elbert, T., Ray, W.J., Kowalik, Z.J., Skinner, J.E., Graf, K.E., & Birbaumer, N. [1994] Chaos and physiology, Physiological Reviews, 74, 1-47.

Hassler, M. & Birbaumer, N. [1988] Handedness, musical abilities, and dichaptic and dichotic performance in adolescents: a longitudinal study, Developmental Neuropsychology, 4, 129-145.

Hebb, D. [1949] 'The Organisation of Behavior', Wiley, N.Y.

Holzfuss,J.& Mayer-Kress, G. [1986] An Approach to Error-Estimation in the Application of Dimension Algorithms , in: Dimensions and Entropies in Chaotic Systems, G. Mayer-Kress (ed.) Springer Series in Synergetics, Vol. 32, 114-122, Springer Verlag, Berlin, Heidelberg, New York, Tokyo.

Layne,S.P., Mayer-Kress, G., J. Holzfuss [1986] Problems Associated with Dimensional Analysis of

Electro-Encephalogram Data , In: Dimensions and Entropies in Chaotic Systems, G. Mayer-Kress (ed.), Springer Series in Synergetics, Vol. 32, 246-256, Springer Verlag, Berlin, Heidelberg, New York, Tokyo.

Lerdahl F. & Jackendoff, R. [1983] 'A generative theory of tonal music', Cambridge, Mass. MIT Press. Series title: The MIT Press series on cognitive theory and mental representation.

Lutzenberger, W., Birbaumer, N., Flor, H., Rockstroh, B., & Elbert, T. [1992a] Dimensional analysis of the human EEG and intelligence, Neuroscience Letters, 143, 10-14.

Lutzenberger, W., Elbert, T., Birbaumer, N., Ray, W.J., & Schupp, H. [1992b] The scalp distribution of the fractal dimension of the EEG and it's variation with mental tasks, Brain Topography, 5, 27-34.

Mandelbrot, B.B.[1977] 'Fractals, Form, Chance, and Dimension', W.H. Freeman, San Francisco.

Martin Gardner,' White and brown melodies, fractals and 1/f fluctuations' Scientific American, 238, April, 16

Mayer-Kress, G., A. Hübler [1990], Time evolution of local complexity measures and aperiodic perturbations of nonlinear dynamical systems , in: Measures of Complexity and Chaos, N.B. Abraham, A.M. Albano, A., Passamante, P.E. Rapp (Eds.), Plenum, New York, 155-172.

Mayer-Kress, G., I. Choi, N. Weber, R. Bargar, A. Hübler [1993] Musical Signals from Chua's Circuit, IEEE Transactions on Circuits and Systems, Vol. 40, special issue on "Chaos in Nonlinear Electric Circuits", 688-695, 1993

Mayer-Kress, G., I. Choi, R. Bargar [1993] Sound Synthesis and Music Composition using Chua's Oscillator, Proc, NOLTA93, Hawaii, Dec.5-10.

Mayer-Kress, G., R. Bargar, I. Choi, [1994] Musical structures in data from chaotic attractors, Technical Report CCSR-92-14, Proceedings of the International Symposium on the Auditory Display [ICAD92], Santa Fe, NM Oct. 1992, Proceedings Volume XVIII Santa Fe Institute Series in the Sciences of Complexity, Addison Wesley, Reading.

Mayer-Kress, G., S.P. Layne [1987] Dimensionality of the Human Electroencephalogram. In: S.H. Koslow, A.J.Mandell, M.F.Shlesinger (eds.) Perspectives in Biological Dynamicsand Theoretical Medicine, Annals of the New York Academy of Sciences, Vol. 504, 62-86, New York.

Petsche, H., Lindner, K, Rappelsberger, P., & Gruber, G [1988] The EEG: an adequate method to concretice brain processes elicited by music, Music Perception, 6, 133-160.

Pulvermüller, F., Preissl, H., Eulitz, C., Pantev, C.,Lutzenberger, W., Elbert, T., Birbaumer, N. [1994] Brain rhythms, cell assemblies and cognition: evidence from the processing of words and pseudowords, Psychogoquy, 94.5.48

Schupp, H.T., Lutzenberger, W., Birbaumer, N., Miltner, W., & Braun, C. [1994] Neurophysiological differences between perception and imagery, Cognitive Brain Research 2, 77-86.

Sergent, S. [1993] Mapping the musician brain, Human Brain Mapping, 1, 20-39

Winer, B.J. [1971] Statistical principles in experimental design, McGrawhill & Kogakusha, Tokyo.