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Investigation of global and local network properties of music perception with culturally different styles of music ☆

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ABSTRACT

Background: Graph theoretical analysis has recently become a popular research tool in neuroscience, however, there have been very few studies on brain responses to music perception, especially when culturally different styles of music are involved.
Methods: Electroencephalograms were recorded from ten subjects listening to Chinese traditional music, light music and western classical music. For event-related potentials, phase coherence was calculated in the alpha band and then constructed into correlation matrices. Clustering coefficients and characteristic path lengths were evaluated for global properties, while clustering coefficients and efficiency were assessed for local network properties.
Results: Perception of light music and western classical music manifested small-world network properties, especially with a relatively low proportion of weights of correlation matrices. For local analysis, efficiency was more discernible than clustering coefficient. Nevertheless, there was no significant discrimination between Chinese traditional and western classical music perception.
Conclusions: Perception of different styles of music introduces different network properties, both globally and locally. Research into both global and local network properties has been carried out in other areas; however, this is a preliminary investigation aimed at suggesting a possible new approach to brain network properties in music perception.

1. Introduction

In the field of cognition and perception, many studies have investigated the effects of music on brain responses. Some examples of these studies include: comparisons of the similarities and shared processing foundations between music and language [1,2]; assessments of music helping to improve IQ or work efficiency [3–5]; investigations of translating electroencephalography (EEG) rhythms into music [6,7]; and reports on the effects of cultural styles on music perception [8–10]. Event-related potentials (ERPs) were the most studied electrophysiological responses (e.g., P600 responses to cross-cultural expectancy violations [11]). Some recent interesting studies investigating music perception include: observing the musical event-related synchronization/desynchronization phenomenon, classifying EEG responses to self-assessed liked or disliked music [12]; and comparing the network properties of EEG when listening to Guqin music and noise [13]. Network properties can be evaluated with graph theoretical analysis, which has recently been a popular tool in neuroscience since it could reveal the segregation and integration areas of the brain [14,15]. Graph theoretical analysis first became popular for functional magnetic resonance imaging (fMRI) and diffusion tensor imaging (DTI) studies, and extended to various modalities of brain imaging techniques, such as EEG, near-infrared reflectance spectroscopy (NIRS) [16], and magnetoencephalography (MEG) [17], among others. Graph theoretical analysis usually starts with the construction of a network consisting of vertices that are linked by edges. The vertices stand for elementary units, such as cortical areas or channels, while the edges represent associations between vertices. Regarding the associations, there are many choices, for instance, phase coherence, synchronization likelihood and phase lag index (PLI). Various properties can be calculated from the constructed network, such as clustering coefficient (the most elementary measures of local segregation), path length (an index reflecting the overall integration of the network),

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and efficiency (computed as the average of the inverse of the distance matrix), etc. In most cases, the functional brain would present as a ‘small world’, with a high clustering coefficient and a low characteristic path length, which reflect efficient information spreading, rapid synchronization and low wiring cost [18,19]. However, brain network properties can be affected by many factors, such as age [20], disease [21–25] and alcohol [26], and can reflect different brain activities in different experimental tasks [27–29]. Therefore, graphic analysis is prevalently used to explore the coordination of cortical areas in many medical researches and cognition studies [17,23,30–32].

There are only a few studies that use graph theoretical analysis to investigate brain dynamics related to music perception. Jäncke et al. found that people with absolute pitch tend to have increased degrees, clustering, and local efficiency of functional correlations (fMRI) [33], while Sänger et al. demonstrated that playing duets helped enhance the intra-and-between-brain small-world properties (EEG) [34]. Moreover, Varotto et al. made patients with diseases of consciousness listen to pleasant and unpleasant music, with the aim of discovering the differences of network properties compared with normal individuals (EEG). In the control group (six healthy subjects), an increase in the number of network connections was induced by pleasant music; however, clustering coefficient and path length were not affected by the stimuli. In the patient group (five vegetative state patients), two showed stronger synchronization during the unpleasant condition, and decreased values of clustering coefficient and path length during both musical stimuli [35]. Nevertheless, in regard to the perception of different music styles, there has been no study that uses graph theoretical analysis. In this study, the subjects listened to three styles of music: Chinese traditional, light and western classical music, and EEG data were measured. Because the above-mentioned studies proved that listening to Guqin music changed the brain network properties [13] and other fMRI studies found that different cultural music perception would activate different cortical areas [36], we assumed that processing different styles of music would also affect brain network connectivity properties. To test this hypothesis, graph theoretical analysis was applied. Functional connectivity at different electrodes was estimated using the phase coherence method. The whole brain was modeled as undirected weighted graphs for each subject, and then the network topology was investigated. We analyzed global and local network properties, since both of these are very important in network neuroscience [37]. Many of the previous studies [13,35] only assessed the global properties of network topology. In this study, we looked at the local properties, similar to Xue et al. [38].

2. Methods

2.1. Experimental setup and subjects

Ten healthy Chinese male undergraduates, with a mean age of 22.10 years (standard deviation ± 2.25), participated in the experiment and they were all musically untrained and right handed. All of them were properly paid. During the experiment, the subjects were asked to sit in a comfortable armchair with both arms placed on the hand rests. Chinese traditional, western classical and light music, without lyrics, were presented to the subjects via speakers, with the volume normalized. Each style contained 50 excerpts, which were approximately 16 s in length, and the music was played in a random sequence. The subjects were asked to look at the blank screen with a cross in the middle, which would help them to focus their vision.

Fifty-two EEG channels were sampled using NeuroScan SynAmps2™ (Compumedics NeuroScan, Charlotte, NC, USA), with a sampling frequency of 1000 Hz, and E-Prime 2® software (Psychology Software Tools, Inc., Sharpsburg, PA, USA) was used to present the stimuli and synchronize with the sampling software SCAN 4.3™ (Compumedics NeuroScan). For data preprocessing, all the channels were re-referenced to two mastoid channels, namely, M1 and M2. ERPs were cut 150 ms before the onset of music and continued 1200 ms thereafter, and the baseline was corrected according to the first 150 ms. Four channels of electro-oculogram (EOG) were also recorded, which were placed above and below the left eye, and at both canthus. Trials polluted by EOG were deleted, and the remaining data were filtered by a bandpass filter from 0.1 Hz to 30 Hz. The reference channels were excluded, and 50 channels were retained for network analysis purposes, as shown in Fig. 1.

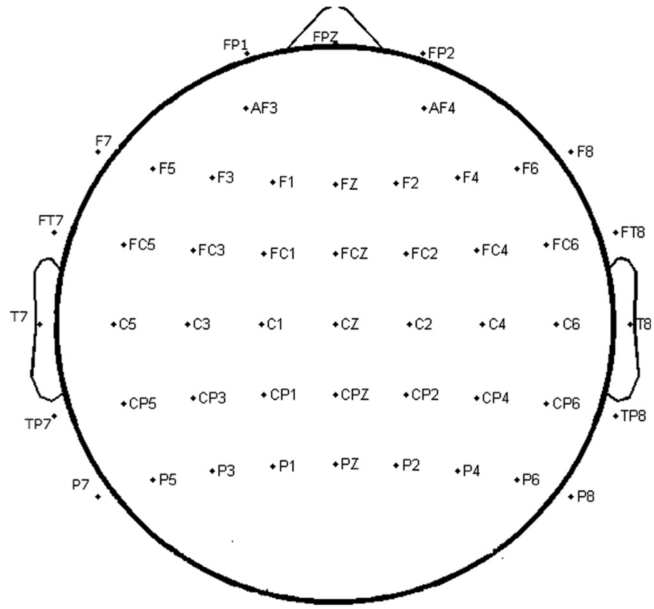

Fig. 1. Fifty electroencephalography channels for graphic analysis.

2.2. Calculation of phase coherence

We compared phase coherence in the alpha frequency band because of its role in music listening, attention and audition [12,39,40]. For each subject, ERP data were averaged over trials, and then the alpha band was filtered (8–13 Hz), denoted as $S(\mathrm{n})$. The analytical signal was

$$S_A(\mathrm{n}) = S(\mathrm{n}) + iS_H(\mathrm{n}) \tag{1}$$

where $S_H(\mathrm{n})$ is the Hilbert transform of $S(\mathrm{n})$.

$$\varnothing(\mathrm{n}) = \arctan\frac{S_H(\mathrm{n})}{S(\mathrm{n})} \tag{2}$$

$\varnothing(\mathrm{n})$ is the instaneous phase of $S(\mathrm{n})$.

For each pair of electrodes x and y,

$$\varnothing_{xy} = \varnothing_x - \varnothing_y \tag{3}$$

phase coherence ω can be calculated as

$$\omega = \sqrt{\left[\frac{1}{N}\sum_{n=1}^{N} \sin{}_n(\varnothing xy)\right]^2 + \left[\frac{1}{N}\sum_{n=1}^{N} \cos{}_n(\varnothing xy)\right]^2} \tag{4}$$

where N is the number of samples in each ERP segment (in our case, $N = 1350$) and ω ranges from 0 to 1; where 0 means uniform distribution of the phase, while 1 stands for strict phase locking.