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Scale-free brain ensemble modulated by phase synchronization*

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Abstract: To listen to brain activity as a piece of music, we proposed the scale-free brainwave music (SFBM) technology, which could translate the scalp electroencephalogram (EEG) into music notes according to the power law of both EEG and music. In the current study, this methodology was further extended to a musical ensemble of two channels. First, EEG data from two selected channels are translated into musical instrument digital interface (MIDI) sequences, where the EEG parameters modulate the pitch, duration, and volume of each musical note. The phase synchronization index of the two channels is computed by a Hilbert transform. Then the two MIDI sequences are integrated into a chorus according to the phase synchronization index. The EEG with a high synchronization index is represented by more consonant musical intervals, while the low index is expressed by inconsonant musical intervals. The brain ensemble derived from real EEG segments illustrates differences in harmony and pitch distribution during the eyes-closed and eyes-open states. Furthermore, the scale-free phenomena exist in the brainwave ensemble. Therefore, the scale-free brain ensemble modulated by phase synchronization is a new attempt to express the EEG through an auditory and musical way, and it can be used for EEG monitoring and bio-feedback.

Key words: Brainwave, Ensemble, Music, Scale-free, Synchronization
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1 Introduction

Electroencephalogram (EEG) is a macro-scale phenomenon of the enormous underlying neuron activities. It has been a useful tool for monitoring the neural electrical activities of the brain in a non-invasive way; however, it is usually represented as visual images or waveforms. A piece of brainwave music might provide us another effective strategy to understand the scalp EEG, by which we can directly 'perceive' what the brain 'sings', or even sings like an ensemble from a multichannel EEG.

In fact, researchers have long been attempting to listen to the hidden brain activities from scalp EEG. The earliest attempt to hear brainwaves was made by Adrian and Matthews (1934). A 'Music for Solo Performer' was later presented in 1965 (Rosenboom, 1976), and other similar music pieces followed. In most of these early works, however, only the amplitude of the alpha waves or other simple and direct characters of EEG signals were utilized as the sources of the musical sound. In the 1990s, various new music generating rules were created from digital filtering or coherent analysis of EEG (Rosenboom, 1999).

The technologies of brainwave music could fall into three categories. The first category is called 'sonification', which translates a few parameters of EEG into the characteristic parameters of music (Rosenboom, 1976; Hinterberger and Baier, 2005; Hermann and Baier, 2013; Väljamäe *et al.*, 2013), or utilizes specific events such as interictal epileptic discharges as triggers for the beginning of music tones or other sound events. Usually, the transformation is

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based on subjectively defined translation rules (Hinterberger and Baier, 2005; Baier *et al.*, 2007; Wu *et al.*, 2010). The second category is the musical application of brain-computer interface (BCI) (Klonowski *et al*., 2009; Miranda, 2010), where the induced EEG changes were utilized to trigger predefined music events. The third way is the scale-free brainwave music (SFBM) technology developed by Wu *et al.* (2009), which is based on the power law of both EEG and music, and tries to translate the brainwave to music according to the intrinsic properties of both EEG and music. The SFBM technology was also utilized to make music of simultaneous EEG and functional magnetic resonance imaging (fMRI) recordings where the fMRI signals were used to modulate the volume of the music (Lu *et al.*, 2012).

Basically, if the temporal power spectrum of the oscillation activity follows a straight line when plotted in coordinates of log power versus log frequency: $S(f)\propto f^{-\alpha}$ ($0<\alpha<4$), it is called a 'scale-free', 'fractal' dynamics, or 'power law' distribution, which is also commonly referred to as '$1/f$ noise' (Grigolini *et al.*, 2009; He *et al.*, 2010). Recent biomedical studies also revealed that the power law exists at almost all levels of neural physiology, including that of ion-channels (Lowen *et al.*, 1999), inter spike intervals (ISI) (Teich *et al.*, 1997), populations of local field potentials (LFPs) (Beggs and Plenz, 2003; Palva *et al.*, 2013), scalp EEGs (Freeman *et al.*, 2006), signals of fMRI (Ciuciu *et al.*, 2012), human movement (Torre and Wagenmakers, 2009), and human social behaviors (Chen *et al.*, 1997). Interestingly, the power law also appears applicable to music: the power spectrum of music audio signal shows a power law distribution (Voss and Clarke, 1978); the note frequency in music has fractal geometry (Hsü and Hsü, 1990; 1991; Liu *et al.*, 2013); the number of occurrences versus the rank of the occurrences of the notes in music pieces follows the power law (Zipf's law) (Manaris *et al.*, 2005; Schroeder, 2009); the rhythm of the music obeys $1/f$ structure through different composers and genres (Hennig *et al.*, 2011; Levitin *et al.*, 2012); and the music has a scale-free network structure (Liu *et al.*, 2010). The scale-free dynamic behavior could reflect the genuine brain mechanism, an exceptionally interesting science field. Furthermore, from an artistic perspective, the brain coordinates various brain activities just like the way different instruments are organized in an orchestra. Although the mechanism at the neuron or column level is tremendously complex, the macro-scale behaviors are harmonious. Meanwhile, there are similarities between the waveforms of the scalp EEG and a music audio signal, both of which may reflect certain typical mental states. The possible intrinsic relation between them has constantly attracted research attention.

The simplest approach to obtain music from multichannel EEG data is to put the melodies from each channel together (Vialatte and Cichocki, 2006), which may result in a cacophony of dissonant sounds that are hard to identify. Furthermore, the spatial information of EEG channels should be taken into account (Hinterberger and Baier, 2005; Baier *et al.*, 2007). For example, the data from the left and the right hemispheres could be phonated in the left and right speakers respectively. Usually, certain electrodes were chosen according to the corresponding tasks, and a pair of symmetric electrodes was the general selection referred to the asymmetric monitoring (Hinterberger and Baier, 2005). In a BCI music application, the spatial features are important for mental pattern recognition. Thus, almost all the channels could be utilized for feature extraction. In our previous efforts, we tried to generate brain music for multichannel EEG through a musical filter, which was designed based on music tonality rules (Wu *et al.*, 2013a; 2013b). After the musical filtering, the music notes in a certain key remained. As such musical filters did not represent the relationships between different EEG channels, this approach cannot predict the harmony of music from the multichannel EEGs.

In this study, our previous SFBM technology was extended to an ensemble of two channels from two hemispheres, and the synchronization level of the two channels was involved in the control of musical consonance and intensity. Actually, synchronous brain activities could indicate the functional integration of different brain areas (Banich and Compton, 2010). Thus, we design a musical filter based on the phase synchronous index, and assume that the degree of synchronization of the two hemispheric activities would indicate the consonant/dissonant level of the musical sequences. Furthermore, a consonant play would sound louder than a dissonant play.

In our implementation, initial brainwave music sequences were generated from the two channels from both hemispheres according to the scale-free rules (Wu *et al.*, 2009), which include the mapping method from EEG amplitude to note pitch, the change of EEG energy to note volume, and the period of local EEG event to the note duration. Then the intervals of the two melodies were modulated according to the phase synchronous index (PSI), so that the integrated music would be relatively harmonic chorus music. Finally, the music intensity was further weighted by PSI to indicate the usual coherent enhancement phenomenon. The PSI of both hemispheres was computed by Hilbert transform. To evaluate this new attempt to convey multichannel EEGs in an auditory musical sequence in real time, a few EEG segments were converted into music pieces and the scale-free phenomenon of the resulting music was also analyzed.

2 Methods

2.1 Overview

The method can be applied to both offline and online EEG data. In an offline setting, the method implements in the MATLAB environment. Various ordinary EEG recording systems can be selected. After data acquisition, the EEG data were processed in MATLAB and converted into musical instrument digital interface (MIDI) files.

In an online setting, the system called Chengdu Brainwave Music (CBM) was used (Wu *et al.*, 2011). The EEG of the subject is collected through the electrode cap, and amplified by the amplifier which communicates with the computer by USB interface. Then the data were sent to a message window designed with C language in a Boland C environment for processing and translation. Finally, the musical parameters were sent to the MAX/MSP for music generation.

In this study, the offline data were taken as an example. With collected data, certain ordinary EEG pre-processing (i.e., artifact rejection and band-pass filtering) was utilized. Then the single channel EEG was translated into MIDI sequences, while the EEG PSI of the data from the electrode pairs symmetrically on the two hemispheres was calculated. Finally, we modulated the MIDI sequences according to the PSI. Fig. 1 illustrates the signal flow for the whole procedure.

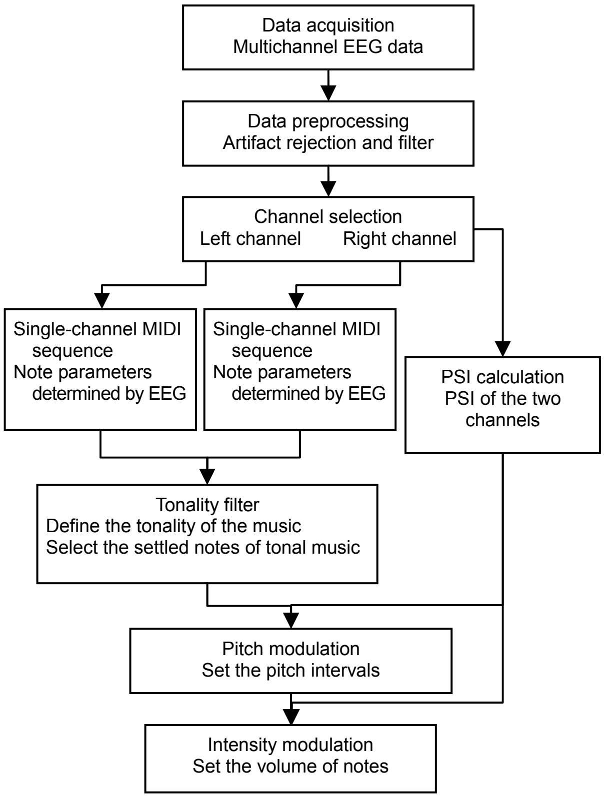

Fig. 1 Signal flow of the scale-free brainwave chorus music generation

2.2 Channel selection

The multichannel EEGs contain abundant brain information. The sonification strategy in this study concerns the phase synchronous relation of the two hemispheres. Thus, the channels locating symmetrically on the left and right hemispheres were selected for music generation (e.g., Fp1-Fp2 and F3-F4). The data from the left and right hemispheres are sonified in the left and right channels of the stereo, respectively.

2.3 From EEG features to musical note parameters

The mapping rule from EEG features to musical note parameters is the key for an EEG sonification strategy. A musical note has four essential parameters: timbre, duration, pitch, and intensity. In this study, the timbre of the piano was used (other instruments are also acceptable), and the duration, pitch, and intensity of a note are obtained from an EEG event period, the wave amplitude, and the change of energy, respectively.

In the proposed method, an EEG 'event' begins when the wave crosses the zero from negative to positive, and ends when the same thing happens the third time. Thus, the duration of the EEG event modulates the duration of musical notes.

The event reflects the information of the EEG fluctuations, which involve multiple physiologic functions, for example, the delta (0.5–4 Hz) and theta (4–7 Hz) waves usually appear in sleep, while the alpha (8–13 Hz) waves are dominant in relaxation with eyes closed, and beta (13–20 Hz) waves mean awake and alert mental states. The period of an EEG event and the duration of notes are both time variables. The simple and direct mapping makes sure that the rhythm of the EEG can be represented by music melody through the combination of the duration of the notes. The music can have the same length with EEG data, which is useful in a real-time system.

The EEG amplitudes are translated into the pitch of the musical notes. The pitch of a note is the logarithm of the fluctuation frequency of the instrument. In the current study, we define the mapping rule from EEG amplitude to pitch according to the scale-free rule of both EEG and music. A power law exists in the relationship between pitch and frequency, and the fluctuation of amplitude can be represented through the change of frequency, so we obtain Eq. (1), which shows the power law mapping rule (Wu *et al.*, 2009):

$$\text{Pitch}=(-40/\alpha)\lg \text{Amp}+n. \tag{1}$$

Here pitch is the number in MIDI (middle C is 60), Amp is the mean of the peak-to-peak value in the EEG event, α is the power-law exponent index which ranges from 0.5 to 1.5, and n is a constant. The value of α could be different in different mental stages, and is computable before the music generating for the offline version. For the online version, α needs to be calculated adaptively. However, it may be set to a constant value during a particular experiment. The details of the derivation of Eq. (1) were referred to Wu *et al.* (2009).

Finally, the EEG power was used to determine the music intensity. Here the music intensity (MI) was assumed to be proportional to the logarithm of the change rate of the average power (AP) according to Fechner's law (Fechner *et al.*, 1966):

$$\text{MI} = k \lg \text{AP} + l, \tag{2}$$

where k and l are constants defined by the range of AP.

Such a definition is based on the psychological fact that stimulus information may not be efficiently conveyed by a habitual signal but by a change. The power is related to the fluctuation which is determined by the note intensity. Eq. (2) has been adopted for single-channel EEG music (Wu *et al.*, 2009). With synchronization information, MI is further weighted by the phase synchronization level, just as

$$\text{MI}_n = 2\gamma\text{MI}, \tag{3}$$

where MI_n is the final music intensity and γ is the phase synchronous index (Section 2.4).

2.4 EEG PSI calculation

Phase synchronization is an important EEG feature, which may provide a platform for binding different sensory attributes and for large-scale cognitive integration (Banich and Compton, 2010). The relation of the two hemispheres is also intriguing. Generally, the left and right hemispheres are functionally lateralized in certain cases, and work together in others (Quiroga *et al.*, 2002). The synchronization of the two hemispheres might reveal their cooperation in various brain functions, and the brainwave music based on multichannels could convey such synergy.

There are several methods to quantify the synchrony degree between the two signals $x(t)$ and $y(t)$; here we choose the one called the phase synchronous index (PSI). The steps are as follows (Quiroga *et al.*, 2002):

Step 1: compute the instantaneous phases $\phi_x(t)$ and $\phi_y(t)$ of each signal using the Hilbert transform:

$$\phi_x(t) = \arctan\left(\frac{1}{x(t)}\int_{-\infty}^{\infty}\frac{x(\tau)}{\pi(t-\tau)}\mathrm{d}\tau\right). \tag{4}$$

$\phi_y(t)$ is obtained in a similar way.

Step 2: define the phase difference $\Phi_{xy}(t)=|\phi_x(t)-\phi_y(t)|$.

Step 3: calculate PSI using

$$\gamma \equiv |< \mathrm{e}^{i\Phi_{xy}(t)} >_t| = \sqrt{< \cos\Phi_{xy}(t) >_t^2 + < \sin\Phi_{xy}(t) >_t^2}, \tag{5}$$

where $<\cdot>_t$ is the mean value of the time window t.

The range of the phase synchronous index γ is from 0 to 1. A γ close to 0 represents very low synchrony, while the synchrony is high for γ close to 1.

To obtain a steady result, the window length of the PSI calculation is set to be 6 s, and the step length is 1 s (Quiroga *et al.*, 2002). Ranging from 0 to 1, the PSI is classified into four degrees. The first class ranges from 0.7 to 1, meaning high synchrony; the second ranges from 0.4 to 0.7, representing middle degree synchrony; the third class ranges from 0.2 to 0.4, meaning low synchrony; and the fourth class is below 0.2. Such classification corresponds to the musical note consonance categories. There are also four classes of different consonance intervals (Section 2.6). The PSI is used to modulate the musical note consonance so that the difference in synchronization can be perceived in an auditory way.

2.5 Tonality filter

After the two single channel brainwave music MIDI sequences are generated, a tonality filter is used to make the music tonal. In the modulation, since there are two notes sounding simultaneously, one note should be settled, while the other is adjusted to a proper pitch according to the PSI.

The rule of the settled note selection refers to some concepts of tonal music, which describe the organization of the note pitch in a scale. This study concerns only the Western major-minor system. An appropriate setting is that the generated brainwave music has a tonality that is in line with the brain mental states. A tonality should be assumed first, before the music generation. In this study, C major is chosen for the example data.

In a tonal music scale, each note has its unique position, and the importance of each note is different. We make a regulation to quantify the importance of the notes in C major scale. For example, the most important and representative tone is note C (importance order is 1), followed by G, E, F, A, D, and B (importance order from 2 to 7). And the importance order of the non-tone notes (#C, #D, #F, #G, and #A) is 8.

In summary, the rule for settled note selection is:

1. Verify the importance order of the two notes from the two MIDI sequences. The smaller one is settled.
2. If the two notes have the same importance order, the one with a greater duration is chosen.
3. If the importance orders of the two notes are both 8, and the PSI is greater than 0.2, the note of the left hemisphere is set to the nearest tone note.

2.6 Pitch modulation

In music, when two notes sound simultaneously, there is a parameter named the harmony interval, which is the distance between their pitches (the frequency of the instruments). The consonance of two notes is determined by their intervals, to be precise by their frequency ratio. It is interesting that the smaller and simpler the ratio is, the more consonant the interval is (Roederer, 2008). For example, when the frequency ratio of the two notes is 1:2 (octave), the two notes sound consonant. The most consonant condition is the unison with a ratio 1:1. In contrast, when the ratio is 15:16, the two notes sound inconsonant. In Western culture, the most common method to classify and name intervals is based on their quality (perfect, major, minor, etc.) and number (unison, second, third, etc.). For instance, an interval of C to E is called a 'major third'. Intervals may also be classified as diatonic intervals and chromatic intervals. In the proposed method, we consider only the diatonic intervals which are between the notes of a diatonic scale. There are 12 different intervals with various numbers of semitones in an octave and these intervals can be ranked according to the harmonic effect (Sposobin, 1959). In Table 1, each interval has a number of harmony consonance rank (HCR). In music theory, the intervals can be divided into four classes. The number of semitones (NS) is used to describe such a classification. The first class includes the unison (NS=0) and octave (NS=12) which are fully consonant (HCR=1); the second class consists of the perfect fifth (NS=7, HCR=2) and perfect fourth (NS=5, HCR=3), very consonant; the third class consists of major third (NS=4), minor third (NS=3), major sixth (NS=9), and minor sixth (NS=8), and the HCR of this class is $4\leq\text{HCR}\leq7$; the last class holds all the inconsonant intervals ($8\leq\text{HCR}\leq12$), such as the major/minor second, major/minor seventh, and all the augmented, diminished intervals.

The EEG PSI describes the mutual relation between the activities of the two symmetric areas on the scalp. Therefore, the modulated harmony of the two notes will show the degree of brain synchronization, which means when the brain areas work in a highly synchronous manner, the corresponding music is quite consonant.

For implementation, the two notes were processed by the tonality filter. The one with prior importance order was chosen, and the other would be adjusted to a more proper pitch according to the PSI. The mapping rule of the interval consonance class and the PSI is shown in Table 1. Every note pair has a PSI value which determines the consonance class of the two notes. The pitch of the note to be adjusted would be changed to match the class of the interval consonance. A 'nearest' principle is considered for the pitch modulation.

For example, if the two notes from the hemispheres are C and D, during the tonality filtering, note C would be settled. If the corresponding PSI is 0.65, which matches the second consonance class (NS=5, 7, HCR=3, 2), the other note would be F (NS=5) or G (NS=7), and then using the nearest principle, note D would be changed to F.

Table 1 The diatonic intervals in an octave

NS	Interval name	HCR	PSI
0/12	Unison/Octave	1	0.7–1.0
1	Minor second	11	0.0–0.2
2	Major second	8	0.0–0.2
3	Minor third	6	0.2–0.4
4	Major third	4	0.2–0.4
5	Perfect fourth	3	0.4–0.7
6	Augmented fourth/ Diminished fifth	12	0.0–0.2
7	Perfect fifth	2	0.4–0.7
8	Minor sixth	7	0.2–0.4
9	Major sixth	5	0.2–0.4
10	Minor seventh	9	0.0–0.2
11	Major seventh	10	0.0–0.2

2.7 PSI and music intensity modulation

We also use PSI to modulate the intensity of musical notes. Eq. (3) shows that the MI is weighted by the value of PSI which was calculated at the time the note was on. So, the large volume means high synchronization while small volume means low synchronization. To the listeners who have no special musical experience, the varieties in intensity are easy and direct to distinguish. In this way, the EEG phase synchronization can be distinguished more easily.

2.8 Experiments

To demonstrate the performance of the proposed brainwave music generation approach, we applied this method to real EEG data. All the EEG recoding experiments were conducted according to the principles proposed in the Declaration of Helsinki, and were approved by the Institutional Review Board of University of Electronic Science and Technology of China (WMA, 1964).

Forty subjects (aged 22.15±2.24, 20 females and 20 males, physically and mentally healthy, and right-handed) participated in the data collection and provided written informed consents. They were seated comfortably in an arm chair and asked to keep quiet. They were advised to relax and think of nothing during the EEG recording with eyes closed (EC) and eyes open (EO) for 3 min each. The signals were recorded by a 16-channel EEG system (Chengdu, China), which was designed by our laboratory, with a sampling rate of 1000 Hz and were band-pass filtered from 0.5 to 40 Hz. The reference was the infinite reference (Yao, 2001; Tian and Yao, 2013). The EEG data with EC and EO were used for music generation.

3 Results

3.1 EEG PSI

We calculated PSI during the two states of all the interhemispheric electrode pairs. The eight pairs are Fp1-Fp2, F3-F4, C3-C4, P3-P4, O1-O2, F7-F8, T3-T4, and T5-T6. The results showed that the PSI values of eyes-closed states were significantly larger than those of eyes-open states at all the electrode locations (T test, p<0.01). With the two-way analysis of variance (ANOVA), the main effects of conditions and electrode pairs are both significant (p<0.01), and the interaction is also significant (p=0.01). The multiple comparison tests show that the electrode pair Fp1-Fp2 is significantly different from the other seven electrode pairs. Pairs F3-F4, F7-F8, T3-T4, and T5-T6 are similar to Fp1-Fp2. C3-C4 is significantly different from the other six pairs except for P3-P4. The P3-P4 is different from the other five pairs except for C3-C4 and O1-O2. The O1-O2 is different from the other six pairs except for P3-P4.

The fluctuation of PSI was also computed using detrended fluctuation analysis (DFA) (Hwa and Ferree, 2002), and significant differences appeared at four positions: Fp1-Fp2, F3-F4, C3-C4, and F7-F8 (T test, p<0.05). Two-way ANOVA shows that the main effects of conditions and electrode pairs are both significant (p<0.05), but there is no significant interaction (p=0.06). The multiple comparison tests show that the electrode pair Fp1-Fp2 is significantly different from the other seven pairs, and has the smallest scale-free exponent. The exponents of F3-F4, C3-C4, P3-P4, and O1-O2 are not distinguished from each other but different from the left four electrode pairs; their exponents are larger than Fp1-Fp2. The F7-F8, T3-T4, and T5-T6 are not different from each other, and have the largest scale-free exponents compared to the other pairs.

The results of PSI and PSI scale-free exponents indicate that the music derived from different pairs of EEG channels might represent the variety of scalp locations and mental states.

3.2 Music from F3-F4 EEG data

Figs. 2c, 2d, 3c, and 3d showed examples of the music of F3-F4 EEG data during EC and EO, respectively. They encompass a wide variety of note pitches. The eyes-closed music has a slightly higher pitch range than the eyes-open music. The results also demonstrated that the eyes-closed music from F3-F4 showed a high level of synchronization (Figs. 2a and 2b), while the eyes-open music showed a low level of synchronization (Figs. 3a and 3b). Therefore, the eyes-closed music involves consonant intervals and large intensity, while the eyes-open music from F3-F4 with large intervals sounds inconsonant and the volume of the piece is small.

For all the 40 subjects, the pitch distributions of eyes-closed and eyes-open conditions are shown in Fig. 4. The pitch ranges of the two states are significantly different (T test, p<0.05). In note duration and intensity, there are also significant differences between EC and EO (T test, p<0.05). For each subject, the pitch, duration, and intensity distributions are unique, but all the terms are in a certain range.

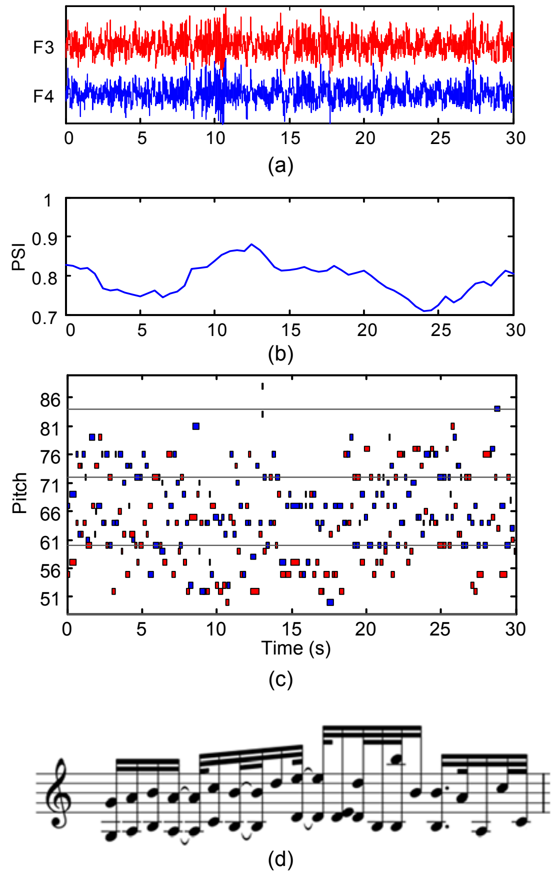

Fig. 2 EEG and musical notes obtained from F3-F4 electrodes with eyes closed
(a) The EEG data from electrodes F3 (left hemisphere) and F4 (right hemisphere); (b) The PSI of the two channels; (c) The notes of the brain music (red from F3 and blue from F4); (d) An example of the music scores. References to color refer to the online version of this figure

Furthermore, the differences between EC and EO in each subject are almost the same, so the music can be distinguished for eyes-closed and eyes-open states.

3.3 Scale-free exponent of EEG and its music

Using the DFA algorithm (Hwa and Ferree, 2002), we found that the scale-free exponent of the EEG data for F3-F4 is 1.22±0.09 (mean±std). Thus, we use α=1.2 in the music generation by Eq. (1) (Wu *et al.*, 2009). Then, the pitch distributions of the brainwave music pieces before and after the integration were also calculated. For eyes-closed music pieces of F3-F4, the scale-free exponent of all the subjects is 1.10±0.11 before the integration, and 1.21±0.10 after. For eyes-open music pieces, the scale-free exponent is 1.02±0.14 before the integration, and 1.13±0.15 after. These results mean that the proposed method retains the scale-free properties of the EEG data. To compare the α values before and after the modulation, we found that the exponents after the modulation (both EC and EO) are significantly larger than the exponents before the modulation (p<0.05). Meanwhile, the differences between the scale-free exponent of EEG and the modulated music are significantly smaller than the differences between EEG and the non-modulated music (p<0.05). In Fig. 5, the music scale-free exponents (α) of the F3-F4 before and after the PSI modulation during EC are shown.

We have computed the scale-free exponent of the HCR curve by DFA. For the condition of eyes closed, the scale-free exponents of all the 40 subjects were 0.53±0.06 before the modulation, while they were 0.64±0.07 after the modulation. The exponents after modulation were significantly larger than those before modulation (p<0.05). Fig. 6 shows the distribution of all the exponents of the subjects. For the condition of eyes open, the scale-free exponents were 0.54±0.11 before the modulation and 0.62±0.08 after the modulation. The difference was also significant (p<0.05) (Fig. 7). These results revealed that the music was more harmonic after the pitch modulation.

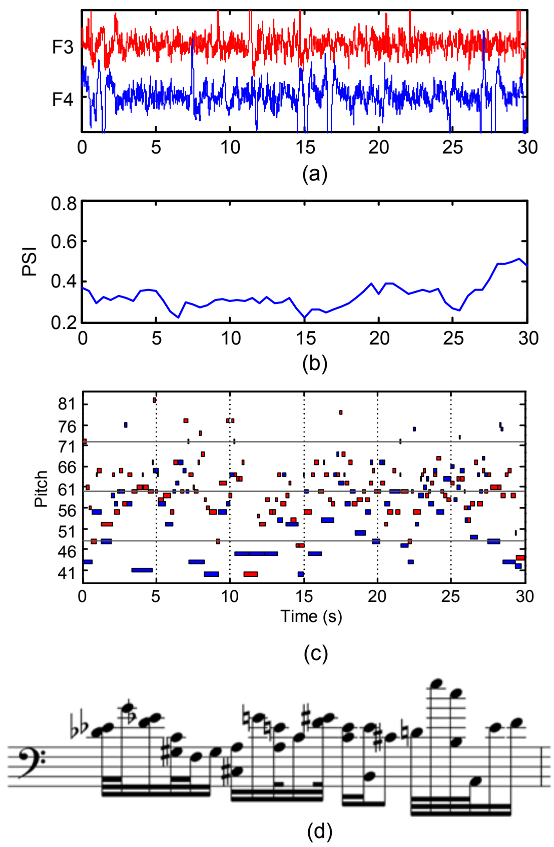

Fig. 3 EEG and musical notes obtained from F3-F4 electrodes with eyes open
(a) The EEG data from electrodes F3 (left hemisphere) and F4 (right hemisphere); (b) The PSI of the two channels; (c) The notes of the brain music (red from F3 and blue from F4); (d) An example of the music scores. References to color refer to the online version of this figure

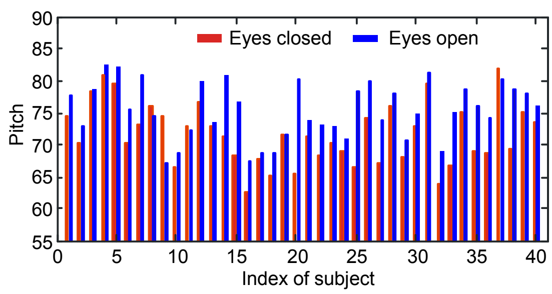

Fig. 4 The pitch distribution for 40 subjects in eyes-closed and eyes-open conditions

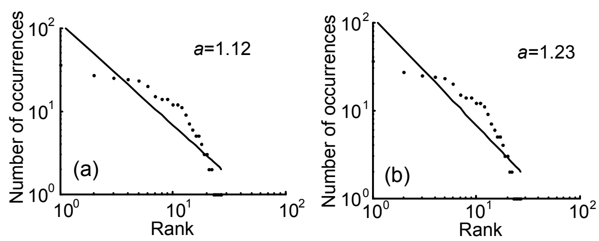

Fig. 5 The scale-free exponent of the brainwave music from F3-F4 during EC before (a) and after (b) the modulation by PSI (obtained from one subject)

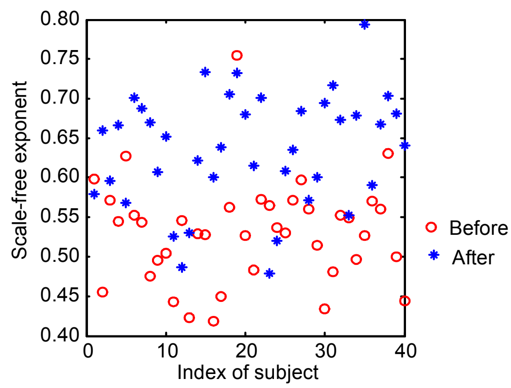

Fig. 6 The scale-free exponents of the eyes-closed brainwave music pieces of 40 subjects before and after the pitch modulation

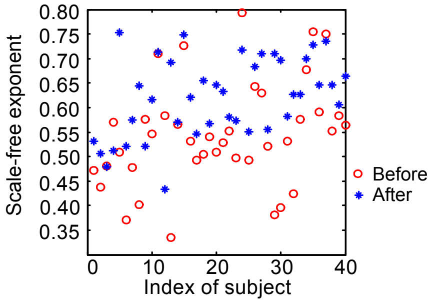

Fig. 7 The scale-free exponents of the eyes-open brainwave music pieces of 40 subjects before and after the pitch modulation

4 Discussion

The above brainwave music derived by our EEG-music mapping rules suggests that the activities of the left and right hemispheres can be represented with ensemble music from two-channel EEG data. The wave details can be heard with a variety of notes, and the synchronization of the hemispheres can be demonstrated by the consonance of the musical intervals and the intensity of the music.

The proposed sonification strategy has advantages for brainwave music generation. First, the method is easy to realize. Thus, it can be used in a real-time system in which the main features of the EEG, such as the amplitude, frequency, especially the change of the synchronization, can be perceived by music. Second, for different mental states, the brainwave music shows different pitch ranges and rhythms. Finally, since the EEG abounds with spatial information, the proposed method is of potential to represent the synchrony of the two hemispheres. In summary, this study shows that significant information of the EEG might be observed and expressed by ensemble music.

Different from other methods mentioned above, we attempt to establish a set of mapping rules to perceive the brain activities in a musical way. Important for emotion expression, the musical interval reflects the cooperation of the notes which exist simultaneously. That is exactly what we want to know about the brain in this study. Meanwhile, the EEG synchrony oscillates slowly, like the music harmony. In our view, there may be an intrinsic relation between brain activities and the music duet. The brainwave music may improve our understanding of this relation.

The brainwave music may give some hints of the underlying neural mechanism. Interestingly, the scale-free exponent of the music is close to the EEG data after the modulation based on the phase synchronization. There is a conjecture that the power law is a criterion of the aesthetics. When the exponent is about 1, people felt 'just right' (Voss and Clarke, 1978). Most classical music shows the power law distribution in pitch, duration, and so on (Manaris *et al.*, 2005). Apparently, if we assume that various music properties may intrinsically satisfy the scale-free principle (Voss and Clarke, 1978; Hsü and Hsü, 1990), music composition rules, such as tonality, which describes the relation of the note frequency, would serve such a principle. Therefore, when we modulate the music notes according to the tonality scale, the relation of the notes is enhanced and leads to larger exponents.

On the other hand, the fluctuations of the dynamical phase synchronization were scale-free (Gong *et al.*, 2003), which may be an intrinsic characteristic of the brain functional activities. It means that different regions of the brain are not always in lockstep. When we use the music to express the brain activities, the scale-free interval consonance makes the melody more vivid and lively. In fact, we computed the scale-free exponents of the HCR for 1191 classical musical movements written by 20 composers spanning the late 16th to the 20th century. The results showed that the fluctuation of HCR was scale-free. This reveals that the brain and music obey the same law indeed, and it may be one of the answers to the question "why people like music".

The proposed method can be used as a tool for EEG monitoring and analysis. By just listening to the brainwave music, the EEG features can be heard. The method also has potential for bio-feedback and entertainment. In trying to adjust the music to be more consonant, the users would learn how to control and modulate their synchronized brain activities.

5 Conclusions

In conclusion, we established a method to translate EEG from two hemispheres into music pieces played by the symmetry areas of the brain based on the scale-free property obeyed by both EEG and music. The parameters of music notes represent the characteristics of EEG. The synchronization of the EEG is expressed by music consonance. Different brain states can be distinguished by such music. The proposed method is new and might be a useful tool in brainwave monitoring and analysis in brain science and clinical studies.

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