POLYRHYTHM IN THE HUMAN BRAIN

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ABSTRACT

Three complementary methods are used to analyze the dynamics of multivariate EEG data obtained from a human listening to a piece of music. The analysis yields parameters for a data sonification that conserves temporal and frequency relationships as well as wave intensities of the data. Multiple events taking place on different time scales are combined to a polyrhythmic display in real time.

1. INTRODUCTION

EEG time series with their broadband Fourier spectra are known to be polyrhythmic, i.e. they result from the superposition of many individual rhythms. In general, these individual rhythms are irregular but can be identified by their dominant frequencies. Examples are the alpha rhythm (between 8 and 13 Hz in adults) which reflects resting activity of the visual cortex; and the theta rhythm (between 4 and 8 Hz) connected with rhythmic activity of the hippocampus and probably also of the thalamus. As far as higher brain functions (like cognitive processes) are concerned, there is accumulating evidence that they can be related to changes of the degree of firing synchronization of collaborating populations of neurons, the so-called neural assemblies [1]. In the scalp EEG the degree of synchronization of cortical activity is reflected in the intensity of a given rhythm and consequently cognitive processing should be reflected in temporal *dynamics* of the respective cortical rhythms. Therefore we decided to sonify the dynamics of multiple EEG rhythms such that their interactions can be perceived.

Our sonification is an attempt to represent the polyrhythmic texture of human cortical activity. Among the many hypothesis available about the connection between mental activity and certain EEG rhythms, we focus on recent evidence for thalamo-cortical interaction. In particular, during semantic memory recall significant power changes were observed in the theta and beta band of human scalp EEG [2]. We therefore decided to sonify the temporal evolution of multiple rhythms in these frequency bands for various EEG channels.

All parameters for frequency, rhythmic patterns and loudness of sound events were extracted from the time series. No musical material was introduced for aesthetic purposes. Thus, rhythmic, harmonic and even melodic patterns that the listener detects can be traced back to the cerebral activity of the listening subject from which the data were recorded.

2. THE EEG DATA

Raw data were provided with 500 samples per second resolution in ascii format as 26 channel EEG with electrodes positioned according to the 10/20 standard. Prior to analysis they were freed from drift and slow waves (<0.5Hz) by a polynomial fit and transformed to average zero and variance 1.

3. ANALYSIS

3.1. Fourier Transform

Fast Fourier transform was applied in form of the spectrogram, i.e. as a running window, to obtain the temporal dependence of powers. Due to the limited validity of this method when applied to short time segments, average powers within frequency bands were calculated. For its use as sonification parameters the results were calculated according to $P_i^{rel} = (P_i - P_i^{tot}) / P_i^{tot}$ where P_i^{rel} is the relative power, P_i is the power of frequency band i in the running window, and P_i^{tot} is the averaged power of the band for the whole time series.

We divided the low frequency range into two bands, 2-4 Hz and 4-8 Hz and the lower beta band between 12 and 24 Hz into 12 "semitone" bands. These powers control the loudness of instruments. The twelve beta sub-bands were in addition used to assign a frequency to a sound event (see below).

Fig. 1 (top) shows the Fourier spectrum of channel T3 with its alpha peak at about 8.8 Hz (probably a young subject), significant power in the delta band (1-4 Hz), and nearly homogeneous power distribution in the beta band (>13 Hz). The lower panel in Fig. 1 shows the temporal evolution of the relative power in the theta band of the same channel.

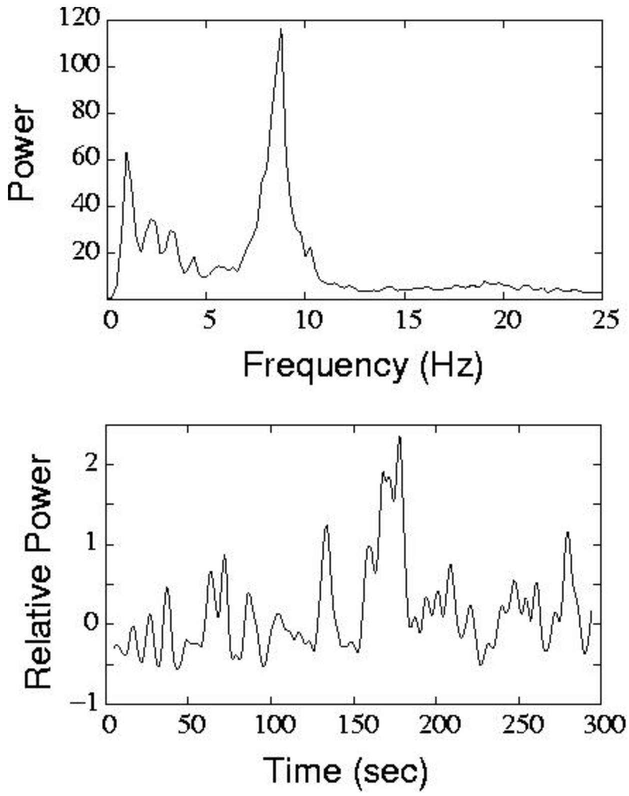

Fig. 1: (Top) FFT of the high-pass filtered time series of channel T3. (Bottom) Time series of the relative power of T3 between 4 and 8 Hz calculated with a running Welch window of 10 seconds and a displacement in steps of 0.01 seconds.

3.2. Delta and Theta Rhyhtms

Due to its suitability for direct representation, the frequency range from 2 to 8 Hz was analyzed for its rhythmic properties (see e.g. [3]). To this end, the corresponding EEG oscillations were converted into sequences of discrete spikes, i.e. signals that allow discrimination between a basal state and an excited state. This was achieved by perturbing an excitable ordinary differential equation with the EEG signal. The method is described in detail in [4] and summarized briefly in [5]. In order to resolve the frequency of the rhythms between 2 and 8 Hz on a semitone scale, a set of 25 "tuned" equations was perturbed in parallel, each adjusted to a different detection frequency on an exponential scale (see [5] for an example of the output of this analysis for one channel). The induced spikes represent the presence of the rhythm with the corresponding frequency and phase in the EEG and are used to trigger a sound event at the corresponding time. In each case an average over 15 runs with different initial conditions was evaluated as the mean spike amplitude. The analysis was repeated for all 26 channels and four (T3, T4, T5, T6) were then selected for sonification.

3.3. Collectivity Parameter

To obtain an objective measure of the degree of collectivity of the whole dataset, we applied a method based on the equal-time correlation matrix. The two-point correlations of all EEG channels were calculated over a window of 4 seconds and this window was shifted over the complete recording with maximal overlap. According to our studies, large values of the smallest eigenvalue of the correlation matrix indicate less collectivity (less synchronization or anti-synchronization between channels) and small values indicate increased collectivity in the EEG [6]. We therefore chose the time series of the smallest eigenvalue as a collectivity parameter.

Fig. 2 shows the temporal evolution of this parameter. Notably, a period of highly collective dynamics is reflected in the low plateau between 160 and 180 seconds. Incidentally, this coincides with the power increase in T3 (see Fig. 1b) and other channels.

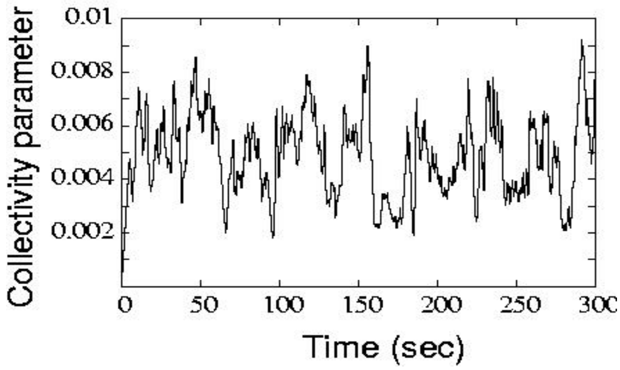

Fig. 2: Collectivity parameter as a function of time.

4. SONIFICATION

For sonification of the results obtained from the described methods of analysis, a four-channel auditory display was chosen, so that the four selected electrodes can be discerned from their source location in the display. For a stereo downmix, we use the left/right separation to reflect activity in the left/right hemisphere, using intensity panning to locate the channels.

As described before, the data were used to compute high-resolved rhythmical information from the method of induced excitations (which generated output at a rate of 333 Hz) as well as melodic information by the semitone-separated Fourier analysis in the beta frequency range of 12-24 Hz. It is already challenging to transport this vast amount of information into a structured audio composition even for a single time series. However, we aimed at portraying the dynamics of the multivariate data for several channels. For the present purpose we restricted the selection to channels T3, T5 (left hemisphere) and T4, T6 (right hemisphere), all placed close to the auditory cortex.

In the sonification, you will hear various acoustic elements. The first is a rhythmically structured pattern of bass tones corresponding to induced excitations in the 2-4 Hz frequency range, using a semitone frequency resolution. Since several of the chains may show induced excitations at the same time, only the one with the maximum activation is picked. Thus, this rhythm is a monophonic sequence. In the submitted sonification, the bass sound is used for T3 and T5 (audible on the left stereo channel), and a pitched percussion instrument, a tom drum, for T4 and T6 (right stereo channel).

Activity in the 4-8 Hz range is sonified according to the same techniques, resulting in a monophonic, rhythmically high-resolved pattern on a higher octave. For better sound separation, another timbre was chosen to represent such spikes, namely a vibraphone for T3 and T5, and a Rhodes sound for T4 and T6. This selection of sounds was motivated by the need of a short transient in order to have a good rhythmical resolution, and at the same time a clear pitch structure, such that any evident harmonic relations are not hidden by the timbre.

The final element of the sonification is the melody channel, containing the time varying short-time Fourier powers in the 12-24 Hz frequency range. This is again one octave, ordered in semitone intervals. Since data analysis was performed using a 10 seconds analysis window, the variation of spectral energy is rather slow, leading to a slowly varying texture. We applied a nonlinear level mapping from spectral energy to sound level, so that any contributions below a threshold of 70% of the maximal energy in the band are suppressed. As a consequence, on the average one to three tones are audible in the melody texture. Good separation of the different channels here is very difficult to achieve, since neither transient structure nor rhythms can be used to assist the separation. However, we allocated different octaves for different channels hoping that (this in combination with the spatial separation) may help the listener. Now the T3/T5 melody streams (and T4/T6, respectively) occupy different octaves at the same waveform.
The T3/T5 melody streams (and T4/T6 respectively) occupy different octaves at the same pitch. So far the melody sonification is the Spectral Mapping Sonification as described in [7], apart from the particular tuning of pitches on a semitone scale. However, here we take one step further by modifying the timbre in the melody stream according to the observed collectivity parameter. For this the following metaphor may assist interpretation: modulations (i.e. detuning, which causes rougher sounds) correspond to non-collective behavior in real physical systems. In the same way, high collectivity ties oscillators together so that the modulations decrease, and thus can be perceived as a cleaner timbre.

Practically the sonification is computed using *Csound*. The output of the nonlinear excitable systems is transformed into score events. The orchestra is composed in this case simply by a hold oscillator instrument and a sample player instruments, both are making use of reverberation and interpolating envelope control to avoid clicks. In order to mark the beginning and the end of the sonification, a percussive signal is used. Note that the melody stream starts to contribute to the sonification at 5 secs, because this is the minimum center of a 10 seconds running window.

5. GENERAL REMARKS

The sonification allows one to perceive the dynamics of four EEG channels in different frequency bands. The rhythms reflect repetitive neural activity in real time and the melodic section conserves frequency relationships (harmonies) of the corresponding activity in the EEG. The polyrhythmic texture of the sound is highly non-trivial. It allows the detection of synchronized/desynchronized events (particularly in the bass and tom drum), appearance and disappearance of rhythmic sequences in the vibraphone and Rhodes sound (the “waxing and waning” phenomenon), and melodic sequences that occasionally accumulate to form dissonant clusters. The highly collective state at around 170 seconds naturally leads to the climax of the piece.

At present we are unable to “decode” the dynamics of human cerebral activity. However, the human ear offers an as yet unexplored means to both intuitively and analytically study this dynamics from a (so far unheard of) point of “view”. The study in [2] indicates that cognitive events are accompanied (or caused) by parallel changes of rhythms at different levels. Our polyrhythmic sonification opens the way to apply musical, and in particular contrapuntal, training of the sense of hearing to the scientific study of the human mind.

6. REFERENCES

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Soundfiles:

Individual channels:

HermannBaierMueller2004-PIT_0.wav
HermannBaierMueller2004-PIT_1.wav
HermannBaierMueller2004-PIT_2.wav
HermannBaierMueller2004-PIT_3.wav

Downmix:

HermannBaierMueller2004-PIT.mp3