THE SONIFICATION OF RHYTHMS IN HUMAN ELECTROENCEPHALOGRAM

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ABSTRACT

We use sonification of temporal information extracted from scalp EEG to characterize the dynamic properties of rhythms in certain frequency bands. Sonification proves particularly useful in the simultaneous monitoring of several EEG channels. Our results suggest sonification as an important tool in the analysis of multivariate data with subtle correlation differences.

Keywords: Sonification, Exploratory Data Analysis, epileptic EEG

1. INTRODUCTION

Rhythm, the periodic change between different modes of activity, is a fundamental concept that is found in many dynamical systems, ranging from the repetition of the yearly seasons to molecular motion patterns, from respiration to the firing of neurons in the brain. Human senses are tuned to analyze a huge range of frequencies in such rhythms, ranging from Terahertz (perceived as the color of light) to Microhertz (due to our memory skills. Amidst this frequency range, auditory perception allows the sensitive detection of rhythms and their changes, e.g. as pitch structure, roughness, beats in a sound, or temporal structure, where the latter is often what is solely understood as rhythm.

The availability of these listening skills (which does not need to be emphasized particularly for the audience of ICAD) suggests the use of auditory displays to investigate rhythmical patterns in other domains. In this paper we present a new auditory display system to sonify multivariate time series, in our case data from the human electroencephalogram (EEG). Different from common methods to obtain an auditory representation of the data (audification, parameter mapping), this new approach employs a model-based element as mediator between data and sound. This mediator is tuned to detect rhythmical properties of the input signal so that it might be regarded as a task-oriented plugin for a generalized analysis framework.

The EEG data used are from patients with a certain type of epilepsy. Epilepsy appears to be an example of a so-called *dynamical disease* with apparently spontaneous transitions from normal brain activity to a qualitatively different, atypical rhythmic mode. Analyzing these data, researchers hope to discover the mechanisms underlying the still poorly understood dynamic transitions. However, to our knowledge, sonification has not been applied in this context yet.

The paper is structured as follows: in Section 2 we introduce a model-based sonification approach to pre-process the time series data for further use in the display. We then present in Section 3 some analysis of the specific properties of epileptic EEG data in terms of their rhythmic structure – a task for which the human ear is well-suited but which is often neglected in standard time series analysis. In Section 4 we explain briefly how the data are recorded and how the key element of the model, an excitable differential equation, works. Sonification examples are provided and discussed in Section 5. An extension of the sonification concept for the analysis of differences in spatial correlation patterns is introduced in Section 6. Finally, we summarize the specific use of the presented approach for the investigation of multi-channel time series with respect to spectro-rhythmical regularities and present an outlook to future work to assist the exploratory data analysis in this aspect.

2. MODEL-BASED TIME SERIES SONIFICATION

Sonification of time series data is the oldest (and due to its similarity to sound signals) most direct domain of auditory data representations. However, a direct playback of data as sound samples, usually denoted as *audification* often fails to let the most interesting attributes stand out in the auditory display. Nonetheless, it is able to provide very interesting information about the data, its variation, and its temporal evolution at the highest possible accuracy. However, when the interest lies in rhythms that take place at a very limited frequency range, like 1–10 Hz, as for instance in our application, intermediate transformations are required in order to map the variations onto a suited audible attribute range. The technique of *parameter mapping* can be applied well in order to achieve such a conversion, as shown in [1], with the technique of Spectral Mapping Sonification. Different and more complex mapping paradigms were also proposed, like the technique of distance matrix sonification, where a distance matrix is computed from spectral vectors of the 20-dimensional EEG time series and analyzed for long range correlations – which correspond to 'interesting events' [1].

The sonification technique presented in this paper, however, deviates from the formerly used schemes in a dramatic way, although it may appear similar at the end. Here, a model, a set of differential equations, is utilized as a mediator between the data stream and the sound obtained from it. In the framework of Model-Based Sonification [2], the data is used for feeding or parameterizing a dynamical system, the sonification model. The model's dynamic behavior is determined by an independent time evolution (sonification time) and by data-dependent interactions which are being imposed on the model. This 'mind of its own' of the model makes it similar to all real-world acoustic systems, e.g. musical instruments. It is a key element that makes real-world sounds so much more complex and appealing than synthetically reproduced sounds. The dynamic reaction of a system under external input provides a holistic system answer to the excitations in form of sound. Our brain/auditory system was tuned by evolution to extract relevant information from this kind of information encoding. Different from previous models, a chain of coupled oscillators is used here, and processes the data as continuous external input. So to say, the data is the 'air that is blown into the virtual flute, resp. sounding object'. This approach maintains the possibilities of task-dependent model-controls, while still offering intuitive interactions with the data under investigation. For instance, the position in the time series or data stream can in principle be navigated without disrupting the acoustic flow emerging from the system. Without any input, the sound decays and stops, as encountered in all sorts of acoustic systems in our environment (perhaps apart from such complex systems as crying babies, where the noise level even increases with lack of energy input...) [1]. In short, the key feature of our approach is the mediation between incoming data and resulting sound by means of a differential equation that can be tuned w.r.t. to the analysis goals.

3. EEG RHYTHMS

We employ scientific sonification as a tool to study rhythms and differences of rhythms in human EEG. In the analysis of human EEG a "rhythm" is conventionally understood to be a regular waveform strong enough to be distinguished from noisy background activity. Since the earliest reports on electric brain activity by Berger [3] these rhythms have caught the attention of investigators because they were thought to represent deterministic components of brain activity. A prominent example is the alpha rhythm, a sinusoidally shaped wave of about 10 Hz that appears in about two thirds of healthy subjects in a relaxed state with eyes closed. The term rhythm is somewhat misleading if one thinks of musical rhythm which is commonly understood to consist of separate acoustic events with non-random inter-event-interval distribution. Thus, in music, rhythm is not represented continuously by oscillatory waves but discretely, for instance by "beats".

The story does not end here, however. Electric signals on the surface of the scalp are the sum of many events. A scalp electrode does not register individual neural activity but integrates over the electric activity of a large number of neurons. If one records the activity of neural ensembles with electrodes inserted in the neural tissue (in animal experiments) one can simultaneously trace the local neural activity and the mean field potential at some distance from the location. Thereby it is found that regular oscillatory mean field behavior typically is due to regular sequences of bursts, that is discrete groups of high-frequency firings (see [4] for an example of firing that leads to the so-called theta rhythm). The bursts are separated from each other by periods of "silence", i.e. times where no (or little) firing occurs. The EEG waveform is the smoothed result of the averaging during both burst activity and silence. Thus a surface rhythm in the EEG in a sense does indeed represent discrete neural events: the burst rhythms of synchronously firing goups of neurons.

4. THE EXTRACTION OF EEG RHYTHMS

Even under constant external conditions there are characteristic rhythmic changes in the ongoing EEG. For instance, in healthy persons, rhythmic activity may appear slow-wave modulated (the "waxing and waning" phenomenon). And in patients with focal epilepsies there are characteristic pre-seizure losses of signal complexity that may be attributed to rhythmic rearrangements. In these and many other cases EEG analysis requires methods that detect and extract such properties. Such methods are available in standard time series analysis. The intrinsic nonstationarity and the spectral richness of human EEG, however, poses an hitherto unresolved problem.

An individual rhythm and relationships between simultaneous rhythms from different scalp sites can best be understood by means of their phases. However, the "phase" of a broad-band signal (the generic case for human EEG) is an ill-defined term. One can at best speak of partial phases of individual components in the Fourier transform of the signal. Nevertheless, estimates of the "instantaneous phase" of broad-band signals based on the Hilbert transform have been proposed as an operative tool, for example to detect relative changes of the degree of synchronization [5]. As these estimates do not allow direct spectral resolution of the partial phases we developed a method that can be used to estimate both frequency and phase of rhythmic events in signals with broad-band Fourier spectra.

Our approach is to use the EEG signal as a local input to an excitable differential equation and to integrate the equation numerically along with the data stream [6]. The differential equation transforms the continuous signal into a sequence of discrete events. Such a procedure has proved favorable to extract rhythmic properties from artificial irregular signals [7] (see [8] for various examples of physiologic data sonified in a similar fashion). The method is described in detail in [9] and we only give a brief overview here.

The differential equation is prepared such that rhythms of a given frequency can be filtered from the rest of the signal. Successful filtering leads to the induction of propagation waves. The propagation waves are easily detected by their suprathreshold amplitudes. As the induction of waves results from a phase-locking between a component of the signal and the oscillations of the perturbed equation, the temporal wave pattern contains phase information. Using an ensemble of model systems "tuned" to different internal frequencies we are able to analyze a range of frequencies in parallel.

To demonstrate how the method works with EEG data we present the analysis of a typical absence seizure of the *Petit Mal* type. The EEG was recorded in the international 10/20 system with a resolution of 256 Hz from a 10 year old male patient. Fig. 1 presents the frequency-resolved temporal pattern of induced excitation waves. This is the output of the differential equation. The result shows a) the dominant frequency as a band of induction between 2.2 and 2.6 Hz; b) a second band with a second frequency between 3.0 and 3.3 Hz; c) the first subharmonic of the dominant frequency at about 1.2 Hz; and d) the typical slowing-down of the two main frequencies and the subharmonic during the attack. This output of the model is used for sonification.

5. THE SONIFICATION OF EXTRACTED EEG RHYTHMS

For an introduction to different strategies of sonification for human EEG see [1]. In the present contribution we apply sonification to better understand the polyrhythmic dynamics of human brain activity.

In order to analyze a section of EEG we use different kinds of

[1] a little joke for the happy father Gerold Baier :-)

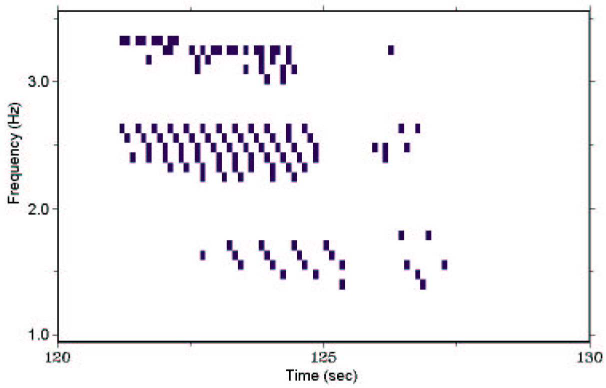

Figure 1: Analysis of the time series of electrode F4 of a patient with absence seizures. Each vertical bar represents an excitation wave induced by the EEG time series.

sonification of the patterns of induced excitation waves. We describe how the signal from one surface electrode is sonified. Then the technique is applied to signals from different electrodes to give an impression of the polyrhythmicity of broad-band EEG. In the following section, an advanced technique is introduced to sonify differences in correlations between EEG channels.

The dynamical system used here actually produces output that cannot be used as sound directly – as one should expect in the case of a sonification model. We therefore have to append a model-variable-to-sound converter. Another way would be to modify the model such that it generates sound signals directly. The first approach is inferior and foils the model-based idea in a way. However, it was chosen because the unmodified model's dynamics is already well understood from prior work [6, 9].

Given the results of an analysis with the method of induced excitation waves (like the one shown in Fig. 1) we have two pieces of information that we would like to sonify. The first is the temporal information: Each excitation wave yields information about the phase of an underlying rhythm in the analyzed EEG. The relationship between subsequent waves defines a temporal ordering that is extracted from the original signal. Thus a representation by discrete events is suitable to make this temporal ordering audible. Therefore we use the result of the analysis to create a time series for each frequency with '1' to denote a detected event (the short vertical bars in Fig. 1) and '0' otherwise.

Secondly, we sonify the spectral information. Each sequence of excitation waves has been obtained with a "tuning factor" for the differential equation. By a linear scaling of the model's response to a sine wave perturbation we can assign a frequency in Hertz to the value of this factor. Yet, the absolute frequency of a given result is not of interest in the present context. Rather, we are interested in relative frequencies. Therefore we arbitrarily chose a base frequency of 261 Hz (c') for the sound that represents events at the lowest frequency of the analysis (e.g. 1.0 Hz in Fig. 1). Then the other frequencies were assigned such that relationships between them and the base frequency were preserved. Thus the sounds that come from the analysis done at 2.0 Hz are one octave apart from that at 1.0 Hz, and so on. The tuning factor was discretized in semitones and the conversion is coupled to the frequencies that the oscillators are tuned to. Thus, a familiar chromatic scale emerges from the temporal system evolution that is suited for the detection of patterns that otherwise remain unaudible in bare audifications.

Sound example 1 (see our website [10]) is the sonification of the results in Fig. 1 with this method. The time scale is roughly real time. The following observations can be made: (i) The analysis filtered all ongoing (non-epileptic) EEG activity, sounds are mostly restricted to seizure activity. (ii) The first sonic events come from the two main frequencies. The subharmonic part sets in later. Using the chosen frequency coding it is easy to attribute the sequence of sounds to the individual contributions. (iii) The slowing-down during the course of the seizure is perceived directly as decreasing average frequency of events. Once this rhythmic and harmonic pattern is understood in its relation to the epileptic time series it is easy to detect the atypical Petit Mal seizure activity in clinical recordings.

Next, we apply a similar sonification strategy to a more typical EEG recording from a second patient. We chose a segment of about 8 minutes prior to an epileptic seizure of the same type as described above. In this period, all recorded time series have the typical broad-band power distribution of childhood EEG. They are highly irregular and there are no salient frequencies as in the case of the absence seizure. Nonetheless, pronounced rhythmic activity is found in the theta and alpha band between 2 and 10 Hz. Fourier analysis of this recording indicates attenuation of power in these two bands in some channels in a period of about 40 seconds preceding the seizure.

We analyzed this period in the same manner as the seizure in Fig. 1. The induction of excitation waves in this case requires stronger coupling of the signal to the differential equation. This reflects the smaller power of individual Fourier components in the chosen theta and alpha frequency band as compared to the seizure period. Fig. 2 shows the temporal information extracted from channels Cz and F4. The induced excitation patterns are highly irregular and, as expected, no single dominant frequencies can be found. Nevertheless, we observe continued rhythmic activity in a band at about 6-9 Hz. This corresponds to a band of maximum power in the Fourier spectra of the time series and appears to be typical for this patient's spontaneous EEG activity.

Sound example 2 is generated with the results shown in Fig. 2. Sonification is as for Sound 1 except that now two channels are presented simultaneously in stereo arrangement. The sonification highlights the respective rhythms and their relative frequencies. Coincidences of beats are easily perceived. In this case, however, no simple relationships between the channels are detectable. The main characteristics is that there is continued activity in the selected frequency band in both channels. A prominent feature of the analysis is the period of about 70 seconds in channel Cz where there is no activity at all.

All 19 channels were analyzed in this fashion. Concentrating on the period of time just before the attack we find that the channels can be grouped in the following way: Group 1: channels that show significant loss of activity in a period of 60 seconds before the seizure. This group consists of channels Fp2, Fz, Cz, T5, O1, and O2. Group 2: channels that maintain or increase their activity 60 seconds prior to the seizure as compared with the average taken over 8 minutes before the seizure. This group consists of channels F4, F7, F8, C4, Pz, and T6. Group 3: the remaining channels with a weak decrease of activity in the preictal 60 seconds. This last group is considered "unspecific" in the sense that neither of the two former tendencies can be attributed unambiguously.

For sound example 3 we sonified the summed activities of the

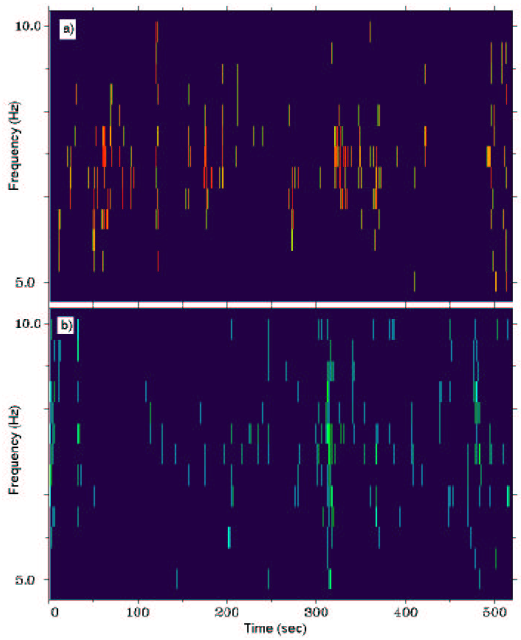

Figure 2: Frequency-resolved analysis of the preictal period of a second patient with absence seizures. The data were from scalp electrode Cz (a) and F4 (b). The seizure occurs at 497-513 seconds.

channels in group 1 (left audio channel) and group 2 (right audio channel). An obvious feature of the sonification is that due to the selection criterion group 1 remains silent in the period corresponding to the 60 seconds before the seizure. Another feature is that the summing leads to a clustering of activities in group 1 while the activities in group 2 remain more evenly distributed. This leads us to assume that the channels in group 1 are more closely correlated than those in group 2. Group 2 channels appear to behave similar to what would be expected for independent noisy signals.

6. THE SONIFICATION OF CORRELATIONS BETWEEN RHYTHMS

The presented model-based analysis plugin provides a spectrally as well as rhythmically structured auditory representation for every single channel resp. time series. An important property of EEG data (which is also frequently prevailing in other data types) is that the data consist of multiple channels whose variations are coupled due to a mixing of 'sources'. The topographical organization of the electrodes on the scalp relates to the brain functioning of localized but coupled brain sub-modules. Besides the temporal evolution of rhythm at a single location on the scalp there may be as well rhythms in the form of changes in the spatial correlations between different channels. Such rhythms are extremely hard to detect from a pure visual analysis of the multi-channel time series, as they may consist of long-term changes of phase relations in different electrodes. However, our auditory system is tuned to detect such patterns in a very similar situation: when listening to a single complex sound, its timbre evolution is determined by the temporal evolution of the harmonics. A change of the 'harmonic structure' can easily be perceived as a timbre evolution: think of the sound of the spoken word 'eye' – it is the change of formants that determines the perceived vowel transition.

The presented sonification model offers various possibilities for extension towards the use of this timbre/rhythm-coupling. As a starting point we discuss our first attempt, anticipating that there will be a wide terrain for further developments.

Instead of chains of nonlinear oscillators used before, each tuned to the detection of a rhythm at one of the semi-tone scale frequencies, we now use a 2D-array of such systems – each column fed by the signal of a different electrode on the scalp. Let us assume an interest in a certain spatial location (e.g. the locus where seizure activity first manifests itself). Then the topographical distance of the other electrodes to the selected coordinate naturally introduces a temporal organization (assuming a run-time for the model-sonification propagating to the listener). In order to obtain sonifications that match our skills to perceive timbre evolutions, the key idea is to relate different channels to different harmonics. Then spatial motion of activation is turned into timbral shape. This may be illustrated by a little example: imagine a signal propagating from frontal to occipital scalp, and using lower harmonics for the frontal and higher harmonics for the occipital region: the spatial pattern of the topographic signal flow is then turned into timbral evolution, audible as an increase in brightness, like a 'wah' as in our next example.

Listen now to sound examples S4.1 (group 1) and S4.2 (group 2), which were synthesized according to this scheme, but with using octave-shifted frequencies for 6 channels: over time, we hear that the timbral evolution of the bursts change – drawing attention to the change of long-range correlations of electrodes, while maintaining the time axis for the analysis of the actual rhythmic structure. A spectrum of the first half of sound example S4.1 is shown in Fig. 3. Obviously, timbral properties are not accessible from the visual respresentation. Actually, the sonification model

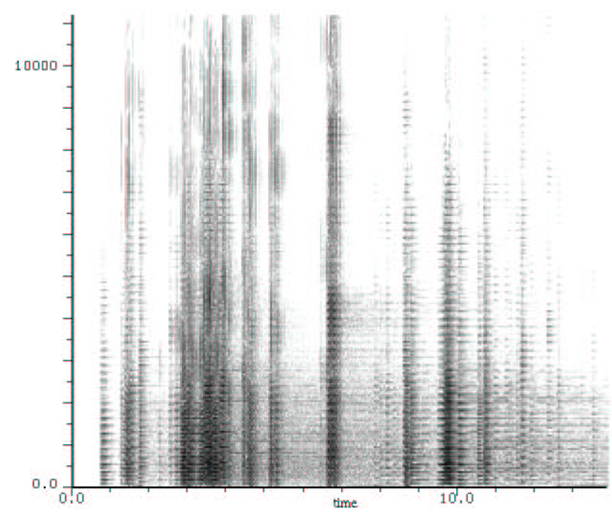

Figure 3: Short Time Fourier Transform of the first 10 s of sound example S4.1. Timbral changes are can be perceived easily whereas they are difficult to detect in the visualization.

implements a multiple use of time within the sonification, a technique known as parameter nesting [11].

We regard this type of structuring – realized in our case by a suited model-based setup – as a step forward to better exploit the differential human perception of timbre, pitch, and rhythm.

7. SUMMARY AND OUTLOOK

We introduced a new approach for sonifying multivariate time series. The key element is an array of excitable non-linear dynamic systems that mediates between the data and the task-oriented representation in the perceptual space. In our case, the task was the exploratory analysis for rhythmical structure. We demonstrated the application of the technique on EEG data from two epileptic patients, in order to better characterize the dynamics leading to seizures. Using sonification it was easy to train the perception of the rhythms of individual EEG channels and to detect characteristic rhythmical patterns that differed between two groups of channels. Our main focus was on the novel technique and only exemplary sonifications were provided. We see the need to evaluate the technique in form of psychophysical tests to assess the use of sonification for the reliable detection of subtle shifts in the polyrhythmic pattern of ongoing EEG. Following this it will be possible to construct special filters to automatically analyze long data streams for these shifts.

Since the 'interesting' regularities are not yet understood, however, it is too early to aim at psychophysical testings. Our next steps will therefore be the optimization of the technique, the inclusion of further task-relevant (e.g. temporal) attributes and the construction of an improved human-computer interface that allows fast and easy navigation and exploration of the data. At a later stage, then, psychophysical experiments are required to assess the use of the display in other domains, e.g. in neurology.

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