Auditory Feedback for Brain Computer Interface Management – An EEG Data Sonification Approach

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Abstract. An auditory feedback for Brain Computer Interface (BCI) applications is proposed. This is achieved based on the so-called sonification of the mental states of humans, captured by Electro-Encephalogram (EEG) recordings. Two time-frequency signal decomposition techniques, the Bump Modelling and Empirical Mode Decomposition (EMD), are used to map the EEG recordings onto musical scores. This auditory feedback proves to have extremely high potential in the development of on-line BCI interfaces. Examples based on the responses from visual stimuli support the analysis.

1 Introduction

Brain Computer Interface (BCI) techniques have received much attention recently, owing to the exciting possibility of computer-aided communication with the outside world. This is achieved in a non-invasive manner, which poses several important and difficult challenges. In terms of signal processing these include the detection, estimation and interpretation of brain signals, and cross-user transparency [1]. It comes as no surprise, therefore, that this technology is envisaged to be at the core of future "intelligent" prosthetics, and is particularly suited to the needs of the handicapped and paralyzed. Other industries which would benefit greatly from the development of BCI include the entertainment, computer games, and automotive industries, where the control and navigation in a computer-aided application is achieved without resorting to using hands, or gestures. Instead, the onset of "planning an action" recorded from the head (scalp)

B. Gabrys, R.J. Howlett, and L.C. Jain (Eds.): KES 2006, Part III, LNAI 4253, pp. 1232–1239, 2006.

surface, and the relevant information is "decoded" from this information carrier. Notice the is notoriously difficult due to the "blind" nature of the problem, lack of any sort of feedback, and overwhelming noise presence within the signal. Apart from purely signal conditioning problems, in most BCI experiments other issues such us user training and adaptation, which inevitably causes difficulties and limits in wide spread of BCI technology due to the lack of "generality" caused by cross-user differences [2]. To help mitigate some of these issues, we propose to make use of an auditory feedback during BCI training or utilization which will inform the user about the "goodness" of brain activities. In our approach, experiments based on visual stimuli were conducted within the so-called Steady State Visual Evoked Potential (SSVEP) mode. Within this framework, the subjects are asked to focus their attention on simple flashing stimuli, whose frequency is known to cause a physiologically stable response present in EEG [3,4]. In the next step EEG signals are mapped into the auditory domain using two signal decomposition techniques one wavelet based and the other based on a decomposition onto a set of AM-FM basis functions. This way, the proposed multimodal BCI scheme uses the EEGs captured with several electrodes, subsequently preprocessed, and transformed into informative and pleasant artificial music, in order for the user to efficiently control the states of their mind (neurofeedback).

2 Methods

Sonification of EEG signals is a procedure in which electrical brain activity captured from human scalp is transformed into an auditory representation [5]. This paper proposes two novel approaches based on multimodal information fusion, whereby the so introduced "audio" modality provides perceptual feedback, but for which there is no unique generation procedure (see a conceptual diagram of the proposed approach in Figure 1).

We aim at looking at the level of detail (richness of information source) obtainable, and compare the usefulness of two signal decomposition approaches in this context. The first approach is based on a sparse signal representation in the Time-Frequency (TF) domain by standard wavelet transformations and is referred to as the Bump Modeling Sonification (BUS) technique. The second one is referred to as the Empirical Mode Decomposition Sonification (EMDSonic) technique, which rests on the identification of signal's non-stationary and nonlinear features, these also represent different "mind" modalities captured by the sensors. This novel method, as shown later, allows us to create slowly modulated tones representing changing brain activities.

2.1 Bump Modelling for Sparse EEG Sonification

A direct mapping of a signal or its wavelet TF representation onto a music file would produce a highly noisy result, this is due to the nature of EEG signals generation and recording techniques [6]. To reduce such artifacts, and provide a

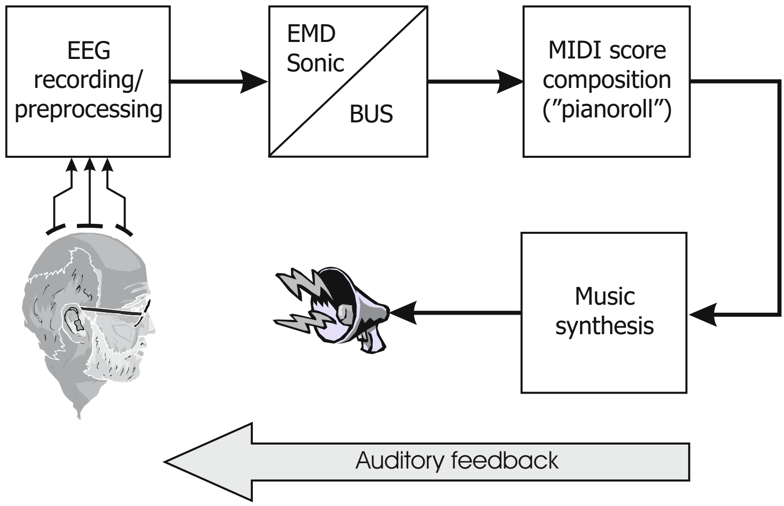

Fig. 1. Block diagram of the proposed EEG sonification scheme for brain computer interfaces. An auditory feedback i.e. a mapping from EEG features onto a discrete set of musical variables, provides a convenient insight into the dynamics and patterns of EEG events.

simplified, yet rich in information representation, the bump modeling technique [7,8] has been proposed, which extracts interesting patterns from the TF maps. The main idea of this method is to approximate a TF map with a set of predefined elementary parameterized functions called bumps, whereby the map is represented by the set of parameters of the bumps. This provides a very sparse encoding of the map, resulting in information compression rates that range from a hundred to a thousand (further details about bump modeling are given in [7,8]). Prior to bump modeling, we compute the so-called "z-score" from the TF map [7]. This way, high normalized amplitude values represent "significant" patterns. Therefore, the bump modeling will extract "interesting" patterns of activity from the background containing the most relevant information in the EEG signal. The algorithm can be outlined in the following steps:

(i) partition the map to define the zones to be modeled (those windows form a set of overlapping areas of the map);
(ii) find the window that contains the maximum amount of energy;
(iii) adapt a bump b to the selected zone, and withdraw it from the original map;
(iv) should the amount of information modeled by the bumps reaches a threshold, stop; otherwise return to (iii).

To isolate "islands" of significant EEG activities, we used half-ellipsoid functions, defined by [8]:

$$\varphi_b(f,t) = \begin{cases} a\sqrt{1-\nu} & \text{for } 0 \le \nu \le 1 \\ 0 & \text{for } \nu > 1 \end{cases} \tag{1}$$

where $\nu = \left(e_f^2 + e_t^2\right)$ with $e_f = (f - \mu_f)/l_f$ and $e_t = (t - \mu_t)/l_t$. The variables μ_f and μ_t are the coordinates of the center of the ellipsoid, l_f and l_t are the half-lengths of the principal axes, a is the amplitude of the function, t and f the time and frequency index.

2.2 Empirical Mode Decomposition for EEG Sonification

Empirical Mode Decomposition (EMD) [10] utilizes empirical knowledge of oscillations intrinsic to a time series is in order to represent them as a into superposition of components with well defined instantaneous frequencies. These components are called Intrinsic Mode Functions (IMF). IMFs, which should approximately obey the requirements of (i) completeness; (ii) orthogonality; (iii) locality; and (iv) adaptiveness. To obtain an IMF it is necessary to remove local riding waves and asymmetries, which are estimated from local envelope of minima and maxima of the waveform. The Hilbert spectrum for a particular IMF allows us to represent in the amplitude - instantaneous frequency - time plane. An IMF satisfies thus the two conditions: (i) in the whole data set, the number of extrema and the number of zero crossings should be equal or differ at most by one; (ii) at any point of IMF the mean value of the envelope defined by the local maxima and the envelope defined by the local minima should be zero. The technique of finding IMFs corresponds thus to finding limited-band signals. It also corresponds to eliminating riding-waves from the signal, which ensures that the instantaneous frequency will not have fluctuations caused by an asymmetric wave form. IMF in each cycle is defined by the zero crossings. Every IMF involves only one mode of oscillation, no complex riding waves are thus allowed. Notice that an IMF is not limited to be a narrow band signal, as it would be in traditional Fourier or wavelets decomposition, in fact, it can be both amplitude and frequency modulated at once, and also non-stationary or non-linear. The procedure to obtain IMF components from a signal, called sifting [10] and consists of the following steps:

- Identify the extrema of the signal waveform $x(t)$;
- Generate "signal envelopes" by connecting local maxima by a cubic spline. Connect signal minima by another cubic spline;
- Determine the local mean, m_1, by averaging the two spline envelopes;
- Subtract the mean from the data to obtain:

$$h_i = x(t) - m_i; \tag{2}$$

- Repeat as necessary until there are no more possible IMF to extract.
- Proper IMF is a first component containing the finest temporal scale in the signal;
- The residue r_i should be generated by subtracting out proper IMF found from the data;
- The residue contains information about longer periods which will be further resifted to find additional IMFs.

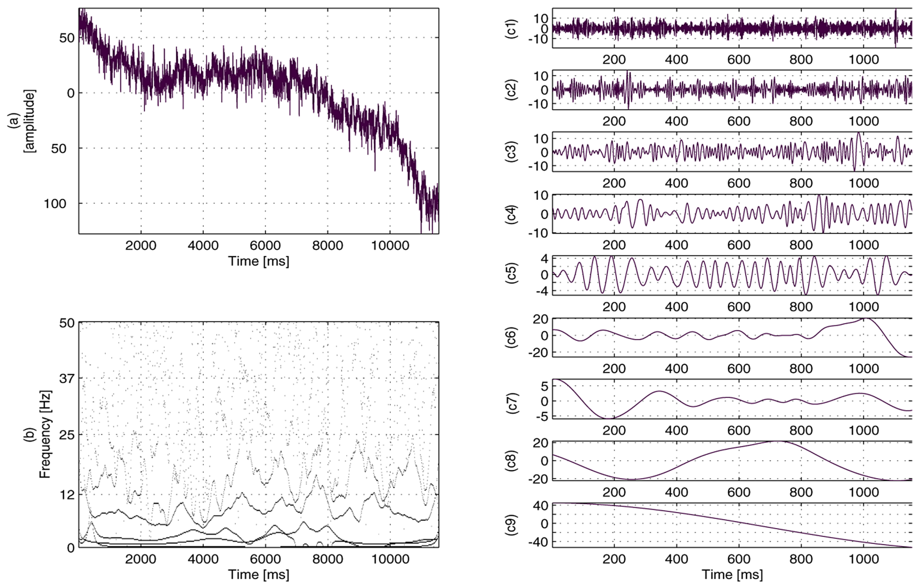

Fig. 2. An example of EEG signal decomposition using EMD technique. Clockwise from top left panel: (a) Raw EEG signal recorded from single frontal (Fp1) electrode. The panels (c1)-(c9) present nine IMF components extracted sequentially IMFs represent oscillations occurring in EEG from higher to lower frequencies. (b) The oscillatory components ranging from 1Hz to 50Hz are combined in form of Hilber-Huang spectrum [9].

An example of EEG data decomposition using the above procedure is illustrated in Figure 2.2 where single channel EEG signal in panel (a) was decomposed into eight oscillatory components as in panel (b) of that figure. It is easy to spot a very low frequency component which represents very slow amplitude drift caused by amplifiers or a loosely connected reference electrode. The higher frequency oscillations are ordered into ascending components. Using the above procedure, EEG signals from chosen electrodes were decomposed separately forming subsets of IMF functions, from which low frequency drifts and high frequency spikes were further removed. From the obtained IMFs corresponding spectrograms were produced by applying the Hilbert transform to each component, as first suggested in [10]. The Hilbert transform allows us to depict the variable amplitude and the instantaneous frequency in the form of functions of frequency and time (in contrast to Fourier expansion, for example, where frequencies and amplitudes are fixed for its bases). Such an approach is very suitable for the non-stationary EEG and subsequent sonification results have slow changing frequency components indicating drifts in phase and amplitudes.

2.3 From Time-Frequency Representation into MIDI

The TF representations of EEG introduced in the above sections can be transformed into musical scores using MIDI procedures [11]. In both cases of EMDSonic or

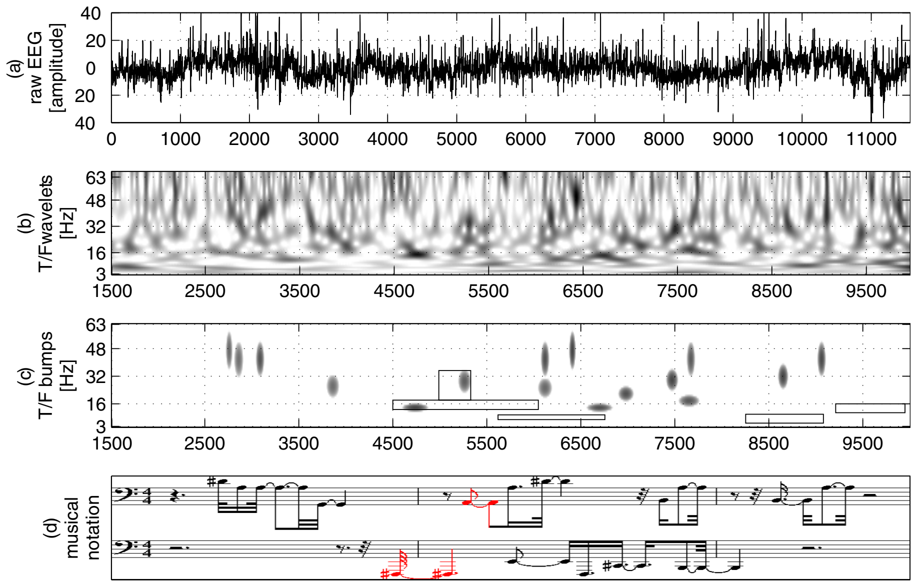

Fig. 3. An example of TF domain bumps modeling for EEG sonification. The above diagrams present: (a) The original raw EEG signal captured during a steady state visual evoked paradigm experiment; (b) wavelets representation the above EEG signal; (c) sparse bump modeling procedure of the above wavelets; (d) is a translation of obtained MIDI representation into classical musical sheet.

BUS TF maps, musical tones were obtained via so called "pianorolls" [11], which directly represent musical scores. In the case of EMDSonic technique, this mapping is performed as shown in Figure 4.(b) and (c), where the Hilbert-Huang spectrum of the original EEG signal is directly mapped by searching for ridges [12]. The location and duration of the ridges is transformed into musical notes with appropriate duration. In case of BUS analysis, the transformation into musical scores is performed as presented in Figure 3: (i) the velocity was obtained from the amplitude a; (ii) the note pitch was obtained following a pentatonic scale (the pentatonic scale is based on five pitch values, for instance: $60 - 63 - 65 - 67 - 70$Hz) from μ_f (for instance, here 3Hz represents pitch 20Hz and 50Hz pitch 70Hz); (iii) the onset of the note was obtained from μ_t using and $l_t/2$; (iv) the duration was computed from l_t.

3 Experiments

EEG sonification experiments were conducted for subjects performing SSVEP based BCI management. Subjects were asked to try to concentrate on a single flashing chessboard whose frequency was later recognized by an separate procedure. The EMDSonic or BUS algorithms were used to inform the user via auditory feedback about the level of concentration in every single trial, which

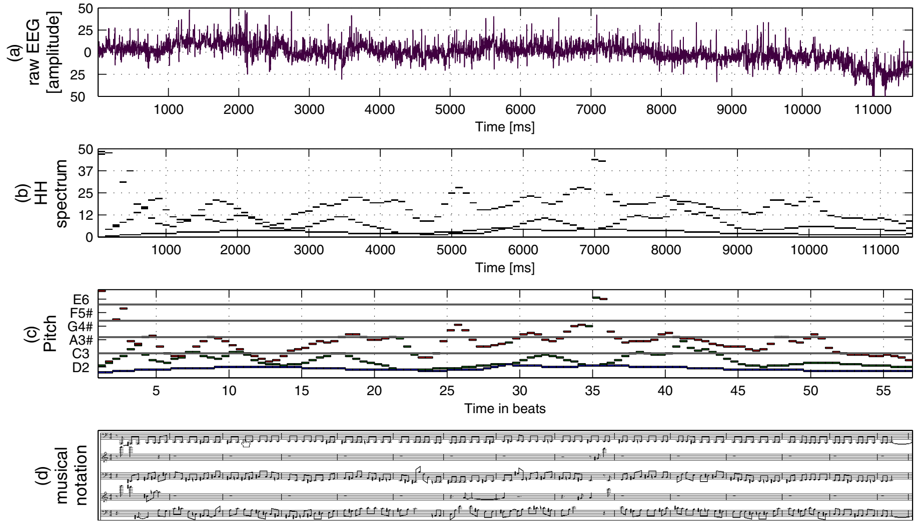

Fig. 4. An example of EMD domain oscillatory components modeling for EEG sonification. The above diagrams present: (a) The original raw EEG signal captured during a steady state visual evoked paradigm experiment; (b) Huang-Hilbert spectrum of the above EEG signal; (c) so called "pianoroll" composed from the Huang-Hilbert spectrogram (similarity of both diagrams in (b) and (c) shows the accuracy of presented EEG to midi sound transformation); (d) is a translation of obtained MIDI representation into classical musical sheet.

is necessary to accurately classify attentionality enhanced frequency of flashing stimuli. Results of EEG sonification using both procedures are depicted in Figure 3 and 4, where same EEG channel and trial was transformed into music. From the figures the differences between the two approaches become apparent.

4 Conclusions

We have presented two approaches to sonify EEG data for direct application in BCI environments. EMDSonic have shown novel and very interesting natural response in auditory domain due to very powerful ability to track slowly varying oscillations in EEG. In online application this approach also introduces delay related to data window analysis and simple decomposition, which is not destructive for monitoring slow cortical potentials in EEG [3]. For EMDSonic it was also easy to segregate MIDI scores into separate channels, later assigned to different instruments, due to filter banks alike EMD decomposition (see middle panel in Figure 2.2). On the other hand more traditional approach using wavelets together with still emerging bumps decomposition allowed us to create very sparse musical scores. Due to a very high computational cost, bump modeling is suitable only for offline EEG sonification. However this limit can be overcome by an extraction of a TF masks, computed from several significant (e.g. training) trials. Both approaches are somehow complementary due to focus on different components in EEG and they provide insights into brain waves visualization and auditory feedback for BCI.

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