Real-Time Wireless Sonification of Brain Signals

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Summary
In this paper, an alternative representation of EEG is investigated, in particular, translation of EEG into sound; patterns in the EEG then correspond to sequences of notes. The aim is to provide an alternative tool for analysing and exploring brain signals, e.g., for diagnosis of neurological diseases. Specifically, a system is proposed that transforms EEG signals, recorded by a wireless headset, into sounds in real-time. In order to assess the resulting representation of EEG as sounds, the proposed sonification system is applied to EEG signals of Alzheimer's (AD) patients and healthy age-matched control subjects (recorded by a high-quality wired EEG system). Fifteen volunteers were asked to classify the sounds generated from the EEG of 5 AD patients and 5 healthy subjects; the volunteers labeled most sounds correctly, in particular, an overall sensitivity and specificity of 93.3% and 97.3% respectively was obtained, suggesting that the sound sequences generated by the sonification system contain relevant information about EEG signals and underlying brain activity.

1. Introduction

One of the interesting multidisciplinary applications of EEG is *sonification*, i.e., converting the brain waves into music.

As far as we know, sonification was for the first time attempted in 1965 by Alvin Lucier (composer) and Edmond Dewan (physicist); in their composition, called *Music for Solo Performer* [3], human brain waves control percussion instruments. Although several researchers and musicians tried to generate sound from EEG signals, there are still many open questions and challenges, and plenty of opportunities. For example, the recent advent of convenient wireless EEG headsets [4-8] may further stimulate and advance the area of EEG sonification.

In this study we design and implement a system that in real-time translates EEG signals, recorded from a wireless EEG headset, into sounds. We assess the sound representations in an offline fashion, by applying our sonification system to EEG collected from Alzheimer's disease (AD) patients and from healthy subjects. The sounds generated from AD EEG should be distinct from sounds extracted from the EEG of healthy subjects. We investigate whether our EEG sonification system improves diagnosis of AD, following an approach proposed earlier by Vialatte *et al*. [9].

The paper is structured as follows. In the next section we explain our methodology. In Section 3 we evaluate our system *offline* by means of an EEG dataset of AD patients and control subjects. In Section 4 we discuss our results and offer concluding remarks.

2. Methods

The proposed sonification system has two operating modes: *offline* and *real-time* sonification. In the *offline* mode, the system extracts sounds from EEG signals that have been recorded earlier. In Section 3, we will apply our system to an EEG dataset from Alzheimer's patients and control subjects, recorded by a wired high-performance EEG system. In *real-time* mode, EEG signals are acquired and immediately transformed into sounds. In the following, we will elaborate on the EEG signal acquisition. Next we will explain how we extract sounds from EEG.

2.1. Data Acquisition

The real-time EEG signals have been collected using a wireless EEG headset, specifically the Emotiv EPOC wireless headset [4] with a sampling frequency 128Hz. The headset has fourteen data collecting electrodes and two reference electrodes. The electrodes are placed approximately at the 10-20 locations AF3/4, F3/4, FC5/6, F7/8, T7/8, P7/8, and O1/2. We used the software package BCI2000 [10] to interface with the Emotiv EPOC wireless headset. The headset transmits encrypted data wirelessly to a laptop computer.

The Emotiv headset is mostly intended for entertainment (e.g., video games) rather than research or medical applications [4]. However, it is inexpensive and user-friendly, and with suitable signal processing, it may become suitable for research and clinical purposes. In particular, the device seems to be prone to various artefacts (such as eye blinking, ECG, EMG, body movements, power sources, etc). In our ongoing work, we are developing real-time algorithms for removing artefacts, which is a crucial step towards reliable real-time EEG sonification.

2.2. Sonification

The system computes the *relative power* in three non-overlapping frequency bands (4-10Hz, 10-20Hz, and 20-30Hz) and generates notes from the computed values. The EEG spectrum is known to depend on the mental state (e.g., relaxation, sleep); moreover, abnormal EEG spectra seem to be associated with neurological disorders, e.g., Alzheimer's disease (AD) [11,12]. We characterize the EEG spectrum by computing relative power in three different EEG frequency bands. Relative power is a simple measure that can readily be computed in real-time. In future work, we will experiment with other spectral measures as well.

We now provide more details on the sonification algorithm. The power spectrum P is calculated for each EEG channel; next *relative power* features f_1, f_2, and f_3 are calculated:

$$f_1 = \frac{P(4-10\text{Hz})}{P(4-30\text{Hz})} \qquad f_2 = \frac{P(10-20\text{Hz})}{P(4-30\text{Hz})} \quad \text{and}$$

$$f_3 = \frac{P(20-30\text{Hz})}{P(4-30\text{Hz})}.$$

Those features are averaged across all channels. The averaged features are then mapped to music notes. To keep the generated sounds as simple and transparent as possible, we considered only notes from one octave (MIDI Octave -1) with pentatonic scale (five notes per octave); we limited ourselves to only one instrument (acoustic bass). Obviously, one could incorporate more music instruments and multiple octaves. However, the extracted sound easily becomes cacophonic and difficult to parse. In the future, we will explore alternative schemes to generate music from EEG relative power. We consider the following three notes and corresponding MIDI note number: (C,48), (E,52), and (A,57). Those 3 notes will be played according to the three values of relative power (f_1, f_2, f_3): If feature f_i is above a certain threshold TH_i, note i is played. More precisely, the notes are generated as follows:

IF $f_1 > TH_1$ THEN play bass note 48

IF $f_2 > TH_2$ THEN play bass note 52

IF $f_3 > TH_3$ THEN play bass note 57.

The EEG is divided in consecutive segments of 1s. In each segment the features (f1, f2, f3) are computed, and notes are generated according to the above rule. Note that at most three notes can be generated for each EEG segment; that occurs when all three features are above threshold. Typically, however, one or two notes are played during each segment, which leads to simple sequences of notes. In future work, we hope to extract more melodic and harmonic compositions, perhaps by mapping features to multiple notes, music samples, natural sounds, etc.

We implemented our sonification system in Python (specifically, pyPortMidi [13] and Numpy [14]). The generated MIDI sequences are synthesized by SyFonOne [15] in conjunction with MIDI-YOKE [16]. The sound sequences are saved into MP3 files for further offline analysis.

3. Evaluation

Our sonification system translates EEG signals into sounds. It is important to verify whether the sounds are representative of EEG. To this end, we conducted a test: We asked several volunteers to use our EEG sonification system for diagnosing Alzheimer's disease. The procedure is as follows. By means of our sonification system, we extract sounds from EEG signals of Alzheimer's patients (AD) and age-matched control subjects. We ask the volunteers to label the generated sounds (AD vs. healthy). If the sounds reliably represent the EEG signals, it should be possible to distinguish sounds generated from AD EEG from sounds extracted from healthy EEG. Interestingly, the volunteers were indeed able to reliably classify the sounds. In the following, we describe our EEG data set; next we discuss the test procedure, and present our results.

3.1. EEG Dataset

We consider EEG data of mild-AD patients and age-matched control subjects. The EEG data set has been analyzed in previous studies [17-19]; the data was obtained using a strict protocol from Derriford Hospital, Plymouth, U.K., and had been collected using normal hospital practices [18]. This EEG dataset is composed of 24 healthy Ctrl subjects (age: 69.4±11.5 years old; 10 males) and 17 patients with mild AD (age: 77.6±10.0 years old; 9 males). The EEG time series were recorded using 21 electrodes positioned according to Maudsley system, similar to the 10-20 international system, at a sampling frequency of 128 Hz. EEGs were band-pass filtered with digital third-order Butterworth filter (forward and reverse filtering) between 0.5 and 30 Hz. For each patient, an EEG expert selected by visual inspection one segment of 20s artifact free EEG, blinded from the results of the present study. From each subject, one artifact-free EEG segment of 20s was extracted and analysed.

3.2. Classification Procedure

A critical issue in our sonification system is the choice of thresholds TH_i. Depending on the application, we can determine the thresholds through various statistical principles. In the application at hand, we determine the thresholds TH_i with the aim of detecting AD EEG. We noticed that relative EEG power has substantially different values in AD patients than in healthy subjects. By appropriately choosing the thresholds, the generated sounds will differ as well. Following this reasoning, we have determined the thresholds as follows:

$$TH_1 = \frac{(\mu_A(f_1) - \sigma_A(f_1)) + (\mu_H(f_1) + \sigma_H(f_1))}{2},$$

$$TH_2 = \frac{(\mu_H(f_2) - \sigma_H(f_2)) + (\mu_A(f_2) + \sigma_A(f_2))}{2},$$

$$TH_3 = \frac{(\mu_H(f_3) - \sigma_H(f_3)) + (\mu_A(f_3) + \sigma_A(f_3))}{2}.$$

where μ_A and σ_A is the mean and standard deviation respectively of the features for AD EEG, and likewise μ_H and σ_H for healthy (control) EEG. Those choices of thresholds can be understood as follows. For example, relative power in the 4-10Hz band is clearly larger in AD patients. Therefore, we choose the corresponding threshold TH_1 below the mean value (of relative power in the 4-10Hz band) for AD EEG and above the mean value for control EEG. As a result, for AD EEG the threshold TH_1 will be reached more often, which will lead to more frequent low-pitch notes (bass note 48). Similarly, AD EEG will yield fewer high-pitch notes (E,52) and (A,57). Now we explain our survey in more detail. We asked 15 volunteers to listen to the generated sounds, and to guess whether they stem from AD patients or healthy subjects. Particularly, we asked each volunteer to classify sound sequences from 10 different subjects (one sequence from each subject). Each volunteer was asked to score the sound sequences from 0 to 10 (0: certainly healthy, 5: unsure, and 10: certainly Alzheimer's). We did not provide any further details about the sound files.

Prior to this test, each volunteer was trained with sound sequences from 4 subjects (2 AD patients and 2 healthy subjects), so that they can learn to appreciate how the sounds generally different in both subjects groups; we also briefly explained how the sounds were generated, and emphasized that, in our sonification scheme, AD EEG tends to generate more low-pitch notes.

3.3. Results

Overall, the volunteers were able to reliably label the sound sequences; they correctly classified 95% of the subjects, with *sensitivity* of 93.3% and *specificity* of 97.3%. Note that we tested just 10 subjects out of 41, and classification on the entire database might be worse. Nevertheless, this experiment demonstrates that the proposed sonification system translates EEG into meaningful sounds, which can for example be used for detecting EEG abnormalities (as in, e.g., AD EEG).

As a benchmark, we conducted linear

discriminant analysis (LDA) with the same features (f_1, f_2, f_3) for the same 10 subjects; we average those features over the entire EEG segment of 20s. In other words, we do not consider here individual EEG segments of 1s. We compute classification rates through leave-one-out crossvalidation. It is noteworthy that through this approach, at most 90% of the subjects are correctly classified. In contrast, our sonification system yielded classification rates of 95%.

4. Discussion and Conclusion

In this study we have developed a system that translates EEG signals (acquired by a *wireless* headset) to *sounds* in *real-time*. The proposed sonification system has been validated *offline* by means of a small EEG data set, collected with high quality wired EEG headset.

Interestingly, the results show that the presented sonification algorithm can be used to differentiate *offline*, by listening to their sonified EEG, the subject with the mild Alzheimer's disease from control subjects with 95% accuracy (see samples on internet [20]), and therefore, it seems the *real-time* system can be used as a reliable AD diagnostic tool.

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