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Authors: François B. Vialatte, Toshimitsu Musha, Andrzej Cichocki

Institutes: Riken Brain Science Institute

Corresponding author address: Francois Vialatte, Lab. for Advanced Brain Signal Processing, 2-1 Hirosawa, 351-0198 Wako-Shi, Saitama-Ken, Japan.

Short title: Sparse Bump Sonification for Multichannel EEG

Sparse Bump Sonification: a New Tool for Multichannel EEG Diagnosis of Brain Disorders

François B. Vialatte[1], Toshimitsu Musha[2], Andrzej Cichocki[1]

1 – RIKEN BSI, Lab ABSP, Wako-Shi, Japan
fvialatte@brain.riken.jp (corresponding author), cia@brain.riken.jp
2 - Brain Functions Laboratory Inc., Takatsu Kawasaki-shi, Japan.
musha@bfl.co.jp

Abstract. The purpose of this paper is to investigate utilization of music and multimedia technology to create a computational intelligence procedure for EEG multichannel signals analysis that would be of clinical utility to medical practitioners and researchers. We propose here a novel approach based on multi channel sonification, with a time-frequency representation and sparsification process using bump modeling. Specific focus is given to applications in early detection and diagnosis of early stage of Alzheimer's disease. The fundamental question explored in this paper is whether clinically valuable information, not available from the conventional graphical EEG representation, might become apparent through an audio representation. Preliminary evaluation of the obtained music score – by sample entropy, number of notes, and synchronous activity – show promising results.

Keywords: EEG, Alzheimer, sonification, time-frequency, bump modeling

1. Introduction

The purpose of this paper is to investigate utilization of music and multimedia technology to create a novel procedure for EEG multichannel signals analysis that would be of clinical utility to medical practitioners and researchers. Sonification is the presentation of information as non speech sounds. Vision is the most important sense for human perception of space, however audition also convey useful complementary information in the time domain. Standard visually-based methods of analysis involve sophisticated processing and filtering of the data, so that by definition some spatial multidimensional aspects are illuminated at the expense of others. This paper proposes a flexible listening sonification system, by which one can adjust sonification to represent different electrodes and time-frequency dynamics: we may for instance consider the brain as an orchestra, where brain regions would represent different musical instruments. From this point of view, analyzing multichannel EEG signals using sounds seems a natural method: using a sonification of EEG signals, we would perceive simultaneously every channel, and analyze more tractably the time dynamics of the signals – hoping to gain new insights about the brain signals. However this metaphor stops here. As a matter of fact, in order to study EEG signals via a sonification process, three constraints for generating sounds should be taken into account:

- it should not loose relevant information,
- it should keep a biological consistency with the original EEG signals (*i.e.* it should be biologically inspired),
- it should be designed for multi-channel EEG, as it is for this use that it will prove the most worthwhile.

The first constraint itself leads to a preliminary question: what will we consider as meaningful within EEG signals? Usually, EEG signals can be studied through several viewpoints (see Fig. 1), the most frequently investigated being:

- EEG signal amplitude (usually in given frequency bands),
- EEG signal oscillatory rhythms (time-frequency study),
- EEG synchronization

Artificial intelligence has many subfields, with varying purposes ranging from the classical "intelligent machine" projects (the GOFAI[1] of Haugeland [1]) to the design of intelligent programs. Our approach belongs to the later domain – and more specifically, a knowledge engineering approach (see e.g. [2]). Knowledge representation and knowledge engineering, when investigated at a sub-symbolic level, is generally referred to as computational intelligence, the most recent offshoot of artificial intelligence (see e.g. [3]). We advocate here a computational intelligence approach, based on the intelligent extraction of relevant information from EEG signals at a sub-symbolic level. We want an intelligent representation of the signal: both sparse and representative of the meaningful features of EEG (amplitude, time-frequency contents, and large-scale synchronization). As a comparison, a direct playback of the EEG (also termed as 'audification') would give an inaccurate representation – furthermore, it would be inaccurate due to inherent noises in EEG recordings [4]. In other words, extracting meaningful information is the key point of our approach.

Furthermore, in order to preserve the consistency of the sonification with the EEG original signal, the sonification process should take into account the signals origin, *i.e.* brain areas the signals are recorded from (occipital, temporal, frontal, parietal, etc.), because these area are not involved in the same functional processes (since about 50 years, we know and have had confirmations that brain areas are functionally organized to deal with several distinct functions). For multichannel EEG this constraint implies an audio representation where each electrode's contribution can be identified. Finally, as human beings have to study the audio output, a tractable representation is mandatory, the last constraint will therefore be to produce sufficiently sparse musical scores. Up to now, few possibilities of sonification for the analysis of EEG data have been addressed: 'spectral mapping sonification' in frequency domain, synchrony study with 'distance mapping sonification' [4]; audio alarm for a surgical instrument [5]; 'model based sonification' for time-frequency (TF) analysis of epileptic seizures [6]; discrete frequency transform for brain

[1] GOFAI = Good Old-Fashioned Artificial Intelligence

computer interface [7] (see also this paper for a review about EEG sonification) – however to the best of our knowledge, none of these sonification process are able to solve all the constraints exposed above, which are required for a satisfactory EEG analysis method. The main purpose of this paper is to propose a new sonification satisfying these conditions, based on a sparse musical transformation of multichannel EEG that we will call bump sonification (BUS).

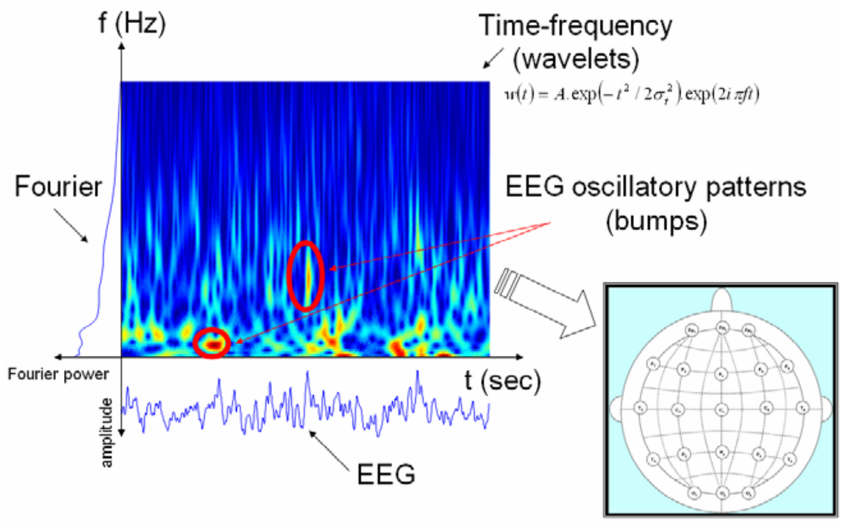

Fig. 1. Possible approaches to study EEG brain dynamics. From the time-domain EEG signal, the spectral information (in frequency or time-frequency) can be extracted. Afterwards, the spatial information is taken into account (using either QEEG, or synchrony measures). However, the time-frequency structure (oscillatory patterns) is not sufficiently exploited.

In the course of a clinical study [8], EEG signals from elderly patients in the early stage of Alzheimer's disease (AD) who developed AD within one year and a half, and from age matched controls were recorded in a 'rest eyes-closed' condition. We will present an application of BUS as a diagnosis method for the discrimination of these two groups of patients.

2. Methods

2.1. Bump modeling

From raw EEG signals, we seek to obtain a representation allowing the listening of EEG records obtained from a multi-channel EEG device. The Bump Sonification (BUS) method (Fig. 2) follows three steps:

- preprocessing, including artifacts removal and dimensionality reduction based on Blind Source Separation (BSS) or Independent component analysis (ICA),
- sparse TF representation,
- music generation (midi files).

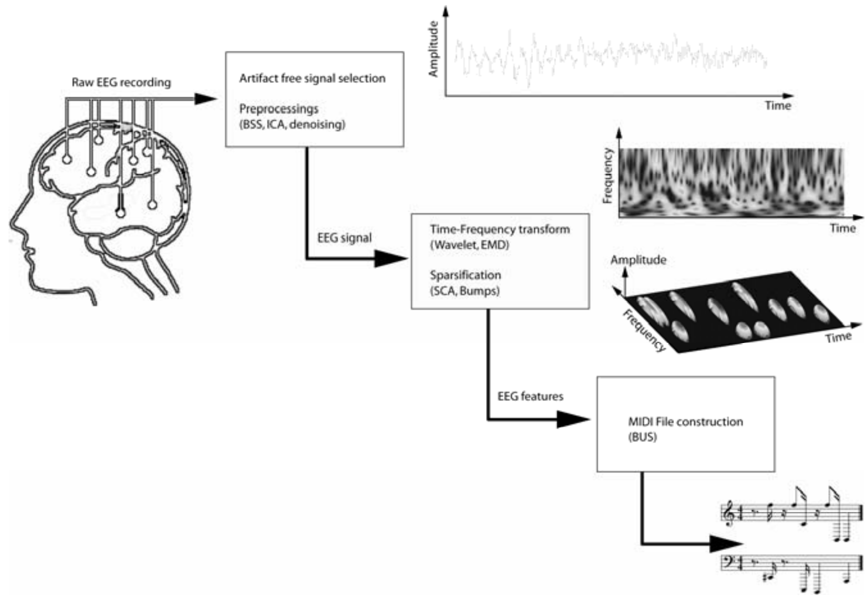

Fig. 2. BUS model. From EEG signals, features are extracted using a sparsification process. TF representation of the signal is obtained, and the features extracted are used to build a MIDI (".mid") music sonification file. Illustrations on the right side are obtained from a scalp EEG record (2 sec, sampling frequency 1KHz): from top to bottom the signal, its wavelet TF representation, its bump model, and the final sonification are represented.

The TF representation is obtain using wavelet transform, with complex Morlet function (Eq. 1), which is highly redundant but however well suited for TF analysis of electrophysiological signals ([9],[10],[11]) because of its symmetrical and smooth Gaussian shape both in time and frequency domains.

$$w(t) = A.\exp\left(-t^2 / 2\sigma_t^2\right).\exp(2i\pi ft) \qquad \textbf{(1)}$$

where t is time, f is frequency, σ_t is the time deviation, and A is a scalar normalization factor. After the wavelet transform, c_{ft} coefficients describing time t and frequency f are obtained along all T time steps and all F frequency steps.
The main idea of the TF sparsification step (bump modeling [12],[13] Fig. 3) is to approximate a TF map with a set of elementary parameterized functions. Bump modeling was performed using the ButIF toolbox, version 1.0 (freely available from

[14]). A bump is adapted under constraints inside a TF window W, in order to minimize (using BFGS algorithm [15]) the cost function C:

$$C = \frac{1}{2} \sum_{t,f \in W} \left(z_{ft} - \beta(f,t) \right) \tag{2}$$

where the summation runs on all pixels within the window, z_{ft} are properly normalized TF coefficients at time t and frequency f, and $\beta(f,t)$ is the value of the bump function at time t and frequency f. In the present application, the TF coefficients c_{ft} where normalized to obtain z_{ft} z-score values by comparison with an average baseline, at each frequency bin f, from Control patients:

$$\forall t, z_{ft} = \frac{c_{ft} - \mathrm{M}_f}{\Sigma t} \tag{3}$$

where M_f is the average of baseline means m_p along time for all Control patients p:

$$M_f = \left\langle \overline{m_p} \right\rangle_p = \left\langle \sum_t^T \frac{c_{ft}^p}{T} \right\rangle_p \tag{4}$$

and Σ_f is the average baseline of standard deviations s_p along time for all Control patients p:

$$\Sigma_f = \left\langle \overline{s_p} \right\rangle_p = \left\langle \frac{1}{T-1} \sum_t^T \left(c_{ft}^p - m_p \right)^2 \right\rangle_p \tag{5}$$

This way, high normalized z_{ft} values represent patterns differing significantly from usual activity (which should convey the most significant information).
Half ellipsoid functions were found to be the most suitable bump functions:

$$\begin{cases} \beta(f,t) = a\sqrt{1-v} & \text{for } 0 \le v \le 1 \\ \beta(f,t) = 0 & \text{for } v > 1 \end{cases} \tag{6}$$

where $v = \left(e_f^2 + e_t^2 \right)$ with $e_f = \left(f - \mu_f \right) / l_f$ and $e_t = \left(t - \mu_t \right) / l_t$.
μ_f and μ_t are the coordinates of the centre of the ellipsoid, l_f and l_t are the half-lengths of the principal axes, a is the amplitude of the function, t is the time and f the frequency.
Thereafter, the most prominent TF features from the artifact free EEG signals are obtained. These prominent oscillations are representative of transient local synchronies of neural assemblies [16]. This BUS model is a general scheme, which was already successfully applied for a brain computer interface application [17]. We will focus here on the application of BUS to the discrimination between PMCI and Control patients.

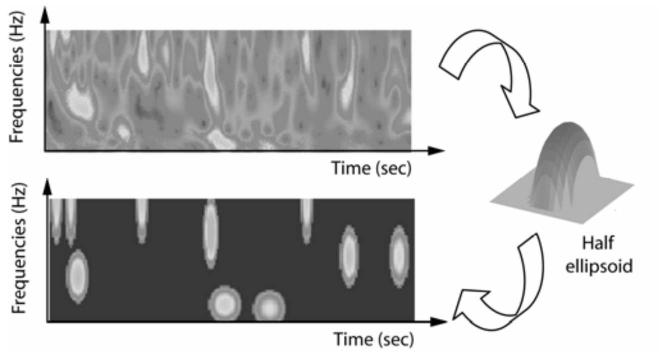

Fig. 3. Bump modeling, example. The TF map (*top*) is modeled by parameterized functions (*right*) into a more tractable model (*bottom*) highlighting the most prominent TF patterns.

2.2. Multi Channel Sonification

When more than one channel is under investigation – for instance, if one seeks to investigate global EEG dynamics, or EEG long-distance synchrony – we propose an approach (Fig. 4) inspired by the brain areas functional significance: if one is to study brain dynamics via EEG sonification, then brain areas whose functionalities are close should be represented by sounds which should be close; whereas brain areas whose functionalities are remote should be represented by easily differentiable sounds.
Therefore, for multi channel EEG representation, the music notes will be defined by the following parameters of the bumps:

- Amplitude of the bump will be converted into velocity of the note played (valued between 40 and 127), *i.e.* how loud the note is played;
- Position of the electrode will be converted into the note pitch (in MIDI format, C4 note = pitch 60) scaled to a pentatonic scale (following pitch progressions such as 60-63-65-67-70) if there is many electrodes, depending on the electrode position on the head (close electrodes have close pitches, remote electrodes have distant pitches).
- Position and width in time of the bump will be converted into onset and duration of the note (in ticks per square).

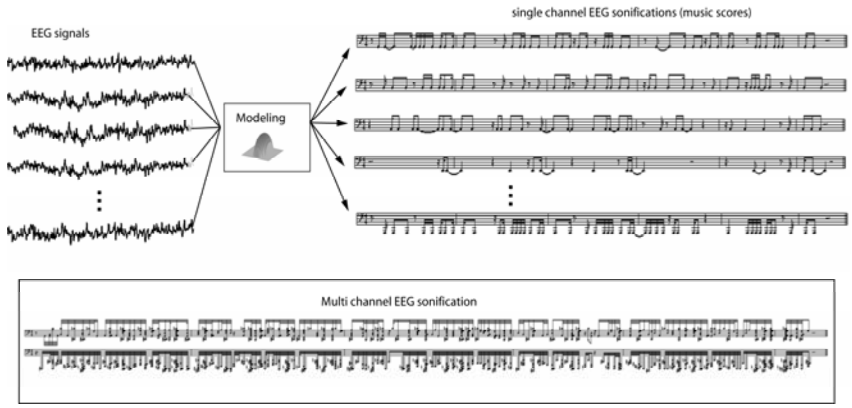

Fig. 4. Multi channel EEG sonification example. This example is obtained from a 21 channel EEG lasting 20 sec, between 5 and 25 Hz. The huge amount of information is synthesized into a music score, and its listening highlights signal dynamics and synchrony.

This representation gives efficient representations of the brain dynamics. However, two caveats should be noticed:

- if the number of electrodes is too high, too much musical information may be produced: the sounds generated would become cacophonic;
- if the frequency span studied is too wide, too much musical information may be produced per channel, which leads to the same problem.

These two situations are different in type, but similar in nature. To avoid cacophony, we propose the following solutions:

- if the number of electrodes is too high, select the most representative electrodes (usually, when several electrodes are used, the signal is redundant) – this may be also obtained by a mathematical reduction (such as ICA projection), however, as we stated in the introduction, the biological realism imposes the constraint to regroup only functionally close electrodes (*i.e.* electrodes belonging to the same brain area), for instance regrouping redundant electrodes from frontal and occipital areas together would lead to a loss of synchrony information; the other solution would be to consider groups of electrodes;
- if the frequency span to study is wide, dividing it into frequency sub-bands to simplify the music scores.

From the bump models, MIDI music was generated using the Matlab MIDI Toolbox [18].

2.3. Online sonification

BUS application to online sonification needs an adaptation of the sparsification procedure: wavelet bump decomposition is time consuming, due to computational costs, which cannot be allowed when real-time result is needed.

Online fast sparsification follows the following methodology:

- offline: select a set of frequency ranges (more than one frequency ranges can be analyzed in parallel); evaluate thresholds;
- online: perform measures on filtered EEG. Apply a smoothing to the absolute value of the signal by convolution of a 4 time-period Gaussian window. Apply Z-score threshold to scale the smoothed curve. When the curve crosses the threshold 1, generate a music note. If the curve does not fall lower than the threshold after 8 cycles, count a second music note. Afterwards, keep generating music notes every 4 cycles. Amplitude of the sparse

For multi channel EEG representation, the music notes will be defined by the following parameters of the bumps:

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- Position and time duration while the curve is over the threshold (max=4 cycles) will be converted into respectively onset and duration of the note (in ticks per square).

This method selects periods in the signal where the EEG activity is sufficiently strong and with an appropriate duration, as can be seen in figure 5.

This approach is less precise than offline bump-based sonification, but retrieves similar results. The procedure for evaluating the z-score parameters is similar as explained in section 2, frequency band selection is performed using preliminary investigations (as in the example shown in figure 6, leading to a reduction of the theta band to 6-8 Hz).

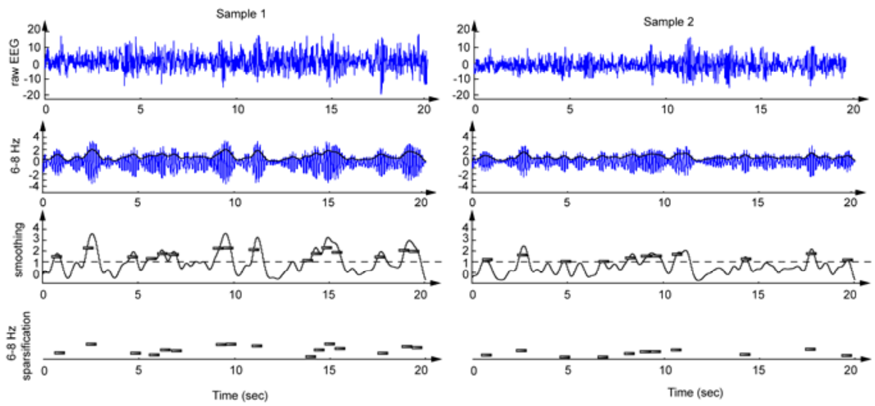


Fig. 5. Two examples of real-time sparsification, in the 6-8 Hz range. Top figures represent the original signal. After filtering, only the smoothed and z-score scaled activity in 6-8 Hz is analyzed (by convolution of a window of 4 time periodes, here 570 msec duration). The final sparse representation (used for online BUS sonification) is displayed at the bottom.

2.4. EEG recordings

Mildly impaired patients progression towards AD (PMCI) and age-matched control subjects were recorded in a 'rest eyes-closed' condition, with electrodes located on 21 sites according to the 10-20 international system. The first continuous artifact-free 20s interval of each recording were used to create two datasets: the PMCI group (n=22) and Control group (n=38). We assessed the capability of BUS to extract significant differences between dynamics of these groups.

As our previous reports [19] about Alzheimer's disease emphasized the importance of the theta range, and because this frequency band is slow (and will therefore give a more tractable representation than higher frequencies) we investigated the records from this database in the theta range (3.5-7.5 Hz), and applied the BUS method described above to generate 60 music scores (22 MCI, and 38 Control music scores).

We intended to highlight synchronization likelihoods uncovered in previous investigations in frontal and parietal areas [20], and therefore gathered the bump modeled from frontal areas (group1 = F3, F3, Fz) and parietal areas (group2=P3, P4, Pz). Low pitches (33, 35 and 37) were associated with group1, whereas high pitches (57, 60 and 63) were associated with group2, following pentatonic scales.

2.5. Paradigm validation

In order to controle the validity of this approach for human-made classification, 5 subjects are trained during 10 to 30 minutes to classify signals from MCI and Control groups. After the training period, the subjects listen to a new database of signals and must attribute a value from 0 to 10 reflecting his opinion about the status of the patient (0 = very MCI, 5 = unknown stage, 10 = very normal). Training and testing sets are non overlapping groups of musical scores selected using *Sy* criterion from the overall database. The validation set contained 10 patients (5 controls and 5 MCI, i.e. 10 musical scores to classify).

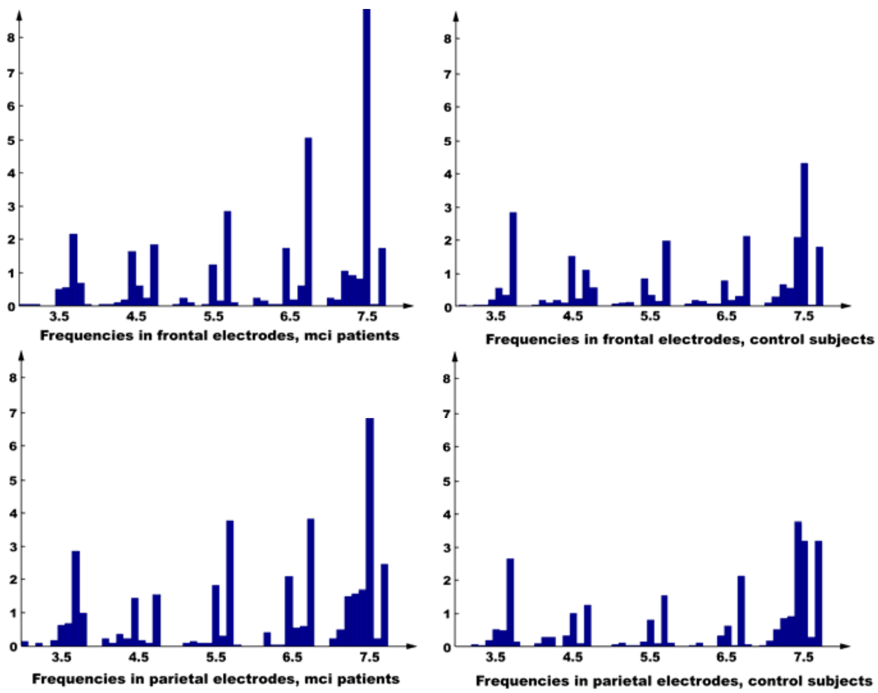


Fig. 6. Histogram of bump frequencies in the theta range, in parietal and frontal electrodes. The most sensible difference between Control and MCI patients is observed in the 6-8 Hz range.

3. Results

3.1. Application to Early Detection of Alzheimer's Disease

The model was assessed with mathematical complexity indexes as well as a perception test in which participants were asked to identify patients with PMCI (progressive mild cognitive impairment) and Control (healthy) by auditory and visual displays. The results show a high degree of accuracy in the identification of PMCI patients from control (healthy) subjects by the auditory displays (see samples available on internet [21]). We thereafter tried to analyze these rhythms divergences, by the computation of different measures of organization (Table 1): sample entropy (predictability of time series [22], Eq. 4-6), number of notes (Eq. 7), and synchronization (Eq. 8).

- Sample entropy is defined by:

$$Sa(m,r) = -\ln(A/B) \tag{7}$$

with

$$A = ((N-m-1)(N-m)/2)A^m(r) \tag{8}$$

and

$$B = ((N-m-1)(N-m)/2)B^m(r) \tag{9}$$

where N is the number of observations in the serie (here N is the total number of notes for the six electrodes), $A^m(r)$ the probability that two sequences will match for m+1 points, $B^m(r)$ the probability that two sequences will match for m points, and r is the tolerance for accepting matches. We used $Sa(2,1)$, therefore we looked upon organization along each different electrodes.

- The number of notes is simply the overall number of notes for the six electrodes.

$$N_o = N \tag{10}$$

- The synchronization measure (Fig. 7) is defined by Equation 5:

$$Sy = \#V / N \tag{11}$$

where #V is the number of notes which own at least one neighbor in the following 200 msec (duplicates are withdrawn), which we deemed to be the largest biologically plausible time window for synchronous activity. We confirmed statistically significant differences between Control and MCI databases with all these measures using the Mann-Whitney statistical test for median differences, the best result being for the synchronization measure.

3.2. Comparison with usual EEG measures

As explained in Section 1, we seek to extract information related with the signal's energy and inter-electrodes synchronization. Sparsification simplifies the complexity of the signal while keeping its most prominent activities. One should then wonder if the information extracted by the bump modeling really provides a different representation as compared to usual measures. In figure 8, scatter plots of *Sy* and *No* against respectively relative Fourier power and magnitude squared coherence show that bump modeling information provides new insights into the structure of EEG signals: *No* is not correlated with Fourier power, while Sy and coherence do not show reliable correlation (r is too small, and after Bonferroni correction the p-value becomes insignificant). Bump modeling removed non relevant background activity, which explains such differences.

3.3. Human classifiers

Our sonification approach has been designed to provide information to human beings, thus computer based analysis is not sufficient to prove its efficiency. In the present section, we will confront our model with human classification.

As shown on figure 9, the classification rate was correct, showing that the classification task was correctly learned by the subjects (one only of the 5 subjects performed poorly; on training as well as on testing set). This was to be expected (classification on the whole database would probably be poorer), however this experiment shows that human beings are capable of classifying EEG signals based on BUS procedure.

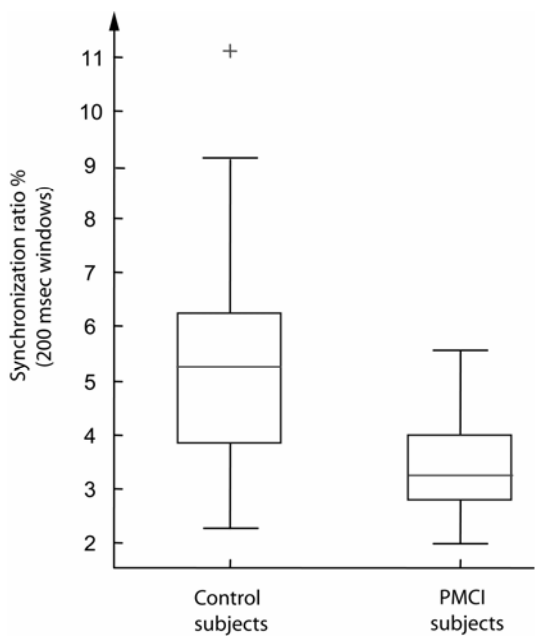
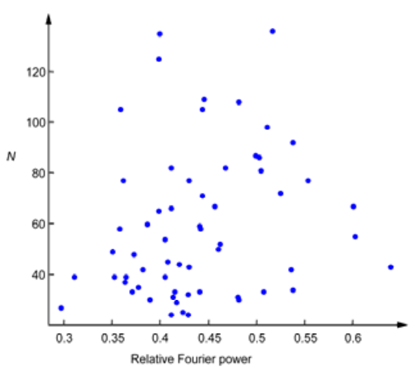


Fig. 7. Box plots of synchronization ratio in percentage, showing significant differences between Control (*left*) and PMCI (*right*) subjects.

Table 1. Results of three measures applied to the music scores from PMCI and Control groups: sample entropy, number of notes, and synchronous activity. Central columns indicates mean and standard deviations of the measures, right column indicates the Mann-Whitney p-value (testing for significant differences of median, highly significant when p<0.01). Synchronization is the most discriminative feature (bold p-value) between PMCI and Controls.

Feature	PMCI	Control	Mann-Whitney p-value[2]
Sa(2,1)	0.66±0.07	0.72±0.08	0.007
No	73.9±28	50.6±26	0.001
Sy (%)	3.52±1.04	5.10±1.96	**4e10^{-4}**



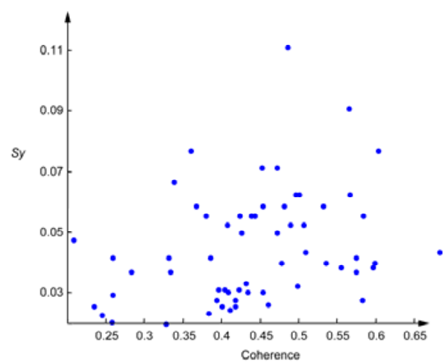


Fig. 8. Scatter plots for measures derived from sonification as compared to more conventional measures. Left: *No* vs. total relative Fourier power in Frontal and Parietal electrodes (r=0.21, p=0.11); right: *Sy* vs. magnitude squared coherence(r=0.31, p=0.02).

[2] For *Sy*, standard deviations are not similar in PMCI and Control sets, as Mann-Whitney test is restricted to similarly shaped distributions we therefore log-normalized in order to obtain closest standard deviations before calculation of the p-value.

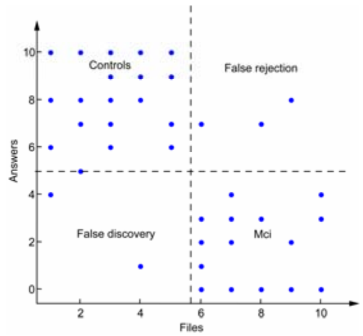


Fig. 9. Result of the experimental human classification, on validation set. The test set is correctly classified, with an error rate of 11%. It is to be noted that all the misclassifications came from the same subject.

Showing that human being are capable of classifying is not sufficient, as the objectives would be:

- a classification of the whole database;
- that human being find this representation to adequately represent the energy and synchronization aspects of EEG signals.

Figure 10 shows that the subjects rating were strongly correlated with each of these measures, thus sonification adequately represented EEG signals.

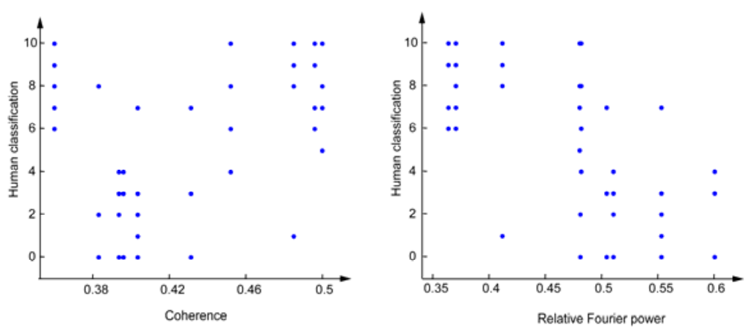


Fig. 10. Scatterplots of coherence and relative Fourier power against human classification. Coherence displays a significant correlation (r=0.45, p=0.001), whereas Fourier relative power displays a significant anti correlation (r=-0.58, $p=10^{-5}$). For coherence plot, the marked group of points is incorrectly correlated.

4. Discussion

We presented a biologically inspired method for multi channel EEG sonification, *i.e.* a method extracting TF components, and transforming these components into music, while keeping consistency with the EEG original signal. EEG signals evolve both with time and space, with a nearly intractable complexity. Consequently, EEG is either analyzed with over-simple models (such as averaging and Fourier power, in which case EEG is not sufficiently specific for clinical applications, see e.g. [25]), or with complex models (in which case the resulting measure representation is impossible in a 3D visual environment). The characteristics of sparse bump modeling carry meaningful information about local and large-scale synchrony (with measures obtained using the stochastic event synchrony model, [23,24]). However, a researcher or a clinician can not rely only on measures; and will certainly not be satisfied with a method providing a number as its only output (for instance, SES provides three output variables, but does not illustrate how these variables are produced). Our sonification approach therefore provides a computationally intelligent illustration of the features of EEG signals[3]; so that human users of a time-frequency-space model of EEG signals can understand the structure of the signal.

This method was proven to be useful on a validation study, where two sets of data (records from patients at the early stage of Alzheimer's disease, and records from age-matched controls) are analyzed in term of musical complexity, and can be discriminated by human hearing. The results obtained concerning the AD early stage diagnosis are consistent with previous studies: brain dynamics evolution related to AD has been reported in several studies using coherence [26], mutual information [28] and synchronization likelihood [20],[29].

This sonification model can be fine-tuned for various frequency sub-bands and reflect unambiguously the oscillatory characteristics of MCI that may not be evident from a visual representation. The improvement of BUS resides in the fact that in contrast to visualization techniques, the temporal patterns extracted in the auditory domain by sonifications are usually better memorized by a trained neuroscientist than visual representations [4]. Our method merges multichannel EEG signals into a time-frequency-space representation (space for electrodes position on the scalp) and is therefore well-suited in order to carry out neurobiological investigations of brain dynamics, not only from a spectral or temporal point of view, but also through other EEG features, such as long-distance synchronization activities [29]. Our experimental results confirm that this approach retrieves reliable and tractable information, and allows a novel approach for AD diagnosis. Since the identification of AD in early stage through EEG recordings is a current priority in neuroscience, sonification may become a valuable component in medical diagnosis.

Further applications, such as sonification for Brain Computer Interface (BCI) researches, could be undertaken – especially using the online sparsification approach. This shall be the subject of our future works.

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[3] For instance, in the above data of 20 sec the dimension is at least 20x8=160 samples per channel at 8 Hz, hence 3360 with 21 channels – and this dimension should be multiplied for each measure applied (amplitude, local and large scale synchrony). The human subjects successfully classified a 10^5 dimension data, which would not be possible (or would be very tedious) with a visual representation.

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