Multichannel EEG Sonification with Ambisonics Spatial Sound Environment

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***Abstract*—When performing complex analyzes on multivariate processes, it is often convenient to utilize various types of visualizations in order to untangle and interpret spatiotemporal dependencies between mixed information streams, and to perform input variable selection. This is particularly advantageous when a level of noise is high, the target of interest information stream changes its spatial location with time, and also for spatiotemporal processes where several streams contain meaningful information, such as in the case of multichannel recordings of electroencephalogram (EEG) based brain activity monitoring which is of a core interest in neurosciences.**

To provide insight into the dynamics of brainwave steady–state electrical responses, a sonification of EEG is proposed, whereby the information about the spatiotemporal steady–state response dynamics is modeled using a spatial sound reproducing ambisonics approach.

Owing to its data–driven and fully adaptive mode of operation, synchro–squeezing transform (SST) is employed as a time–frequency decomposer, and the brain responses to steady–state visual evoked responses (SSVEP) stimuli are sonified. Such perceptual feedback has enormous potential in multichannel brainwave recording analyzes.

I. Introduction

This paper proposes to achieve a *brain electrical activity sonification*, by converting the brainwave source localization features of multichannel EEG into sound images, which are easy to interpret due to their spatial differences. To achieve this, the recorded from the scalp and the relevant information signals should be "decoded" from the multichannel EEG. Spatial sonification of noisy multivariate brainwave signals is of a core interest in neurosciences and neurotechnology applications [1], [2], [3] where visual analysis of the complex experimental recordings is not possible anymore. The brainwave sonification is also very practical in brain-computer interface (BCI) user feedback design [4], [5]. The motivation of the presented study is to test the contemporary non–linear and non–stationary signal separation with the spatial images creation technique in application to multivariate brainwave sonification.

Signal processing challenges in the processing of the brainwave electrical responses are caused mostly due to the non–invasive nature of EEG. The problems include the detection, estimation and interpretation of the notoriously noisy EEG recordings [6], [7], [8]. The set of enhanced EEG features should provide sufficient information for a comfortable signal analysis by human beings; this set should also be large enough to allow for generalization and cross–user differences in cases of larger dataset or brain–computer interface applications [3]. An additional challenge comes from the fact that due to the nature of the information processing mechanism within the brain, the set of features that describes cognitive processes is highly non–stationary and non–linear. The efficient signal visualization engine should be designed so as be real time adaptive in order to accommodate the temporally non–stationary and spatially time varying number of "active information streams" buried in multichannel EEG recordings.

We propose to employ auditory feedback, and thus provide "visualization" of the brain states in the form of a spatial sound images, that is, to perform "sonification" of brain electrical activity. Perhaps the first commercial application of sonification has been in Geiger counters, and sonification has since been considered as an alternative to many standard visualisation techniques. An earlier approach to sonify brain states was our previously introduced single channel EMDsonic [1] and it's multivariate extension [2]. The two above approaches had very high computational costs due to iterative nature of the empirical mode decomposition (EMD) method.

In this paper we make use of the characteristics of human auditory perception, such as the temporal and phase resolutions, to provide simultaneous multichannel sonification of the analyzed EEG. We then analyze the potential of this audio visualization in the representation and understanding of spatial distribution of the steady state visual evoked potentials (SSVEP). The feature extraction from brain electrical responses is performed based on synchrosqueezing transform (SST) [9] and three–dimensional brain sources reconstruction methods (based on brain source modeling, coregistration, forward computation, and inverse reconstruction) implemented in SPM12 brain imaging package [21]. This can create a new alternative to the classical visual data representation techniques when browsing for example the huge amounts of data in search for certain spatiotemporal patterns.

We have conducted the experiments based on visual stimuli. The brainwave recording subjects were asked to focus their attention on simple flashing stimuli, whose frequency is known to cause a physiologically stable EEG responses [6], [10]. This makes SSVEP well suited for neurotechnology applications such as brain–computer/machine interfaces. Next the other

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group of listeners evaluated spatial sonification results by localizing the sound images representing the previously brain identified sources in offline analysis approach.

The paper is organized as follows. The synchrosqueezing transform (SST) is first introduced as a time–frequency analysis technique suitable for the multichannel EEG recordings. The SSVEP response related features are identified which allow to create multiple spatially localized sound images created with three–dimensional brain sources reconstruction method [21] and next played by 23 loudspeakers spatial sphere–shaped audio reproduction using ambisonics [12], [13] environment. Finally, the proposed sonification approach is illustrated within the SSVEP experimental setting.

II. Methods

A. Synchrosqueezing Transform–based EEG Preprocessing and Three–dimensional Brain Sources Modeling

EMD is a technique that aims to decompose a given univariate [14] or multivariate [15] signals into its building block functions. Those functions are the superposition of a limited number of components. The EMD–based techniques have been already successfully applied to artifacts removal from EEG [16], [17], [18], [19], [20]. Unfortunately the EMD algorithm, due to its iterative decomposition nature, is hard to apply in online brainwave analysis applications. A good solution for this problem is the synchrosqueezing transform (SST) method [9], [20]. The SST technique is a combination of wavelet analysis and reallocation methods.

Before explaining details of the proposed implementation of SST to SSVEP responses preprocessing and the sonification, let us review briefly the wavelet and SST techniques. Given the originally recorded EEG signal $s(t)$, its classical wavelet transform $W_s(a,t)$ is obtained as

$$W_s(a,t) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} s(u) \overline{\psi\left(\frac{u-t}{a}\right)} du, \tag{1}$$

where a sets the scale and $\psi(u)$ is the picked wavelet function (Morlet wavelet has been chosen in the implementation discussed in this paper). The wavelet transform does not cause any loosing of any information, so the original signal can be reconstructed as

$$s(u) = D_{\psi}^{-1} \int_{-\infty}^{\infty} dt \int_{-\infty}^{\infty} \psi\left(\frac{u-t}{a}\right) W_s(a,t) \frac{da}{a^2}, \tag{2}$$

with the constant D_{ψ} determined as

$$D_{\psi} = \int_{0}^{\infty} |\Psi(\xi)| \frac{d\xi}{\xi}, \tag{3}$$

with $\Psi(\xi)$ representing the Fourier transform of the chosen wavelet function. Usually the both time and frequency (scale) have the discrete values. Time

$$t_k = k\delta t = k/f_s, \tag{4}$$

where f_s is the sampling frequency of the originally recorded EEG signal. The scale values are usually chosen to be equi–log–spaced (dyadic convention, etc.). The wavelet transform frequency localization at $f_0 = 1$ is often not precise enough to distinguish the frequencies of different oscillatory components so common in the non–stationary and non–linear EEG recordings. It is possible to increase f_0, but that would cause loss in time resolution, causing that some of the oscillations in the frequency of a given harmonic to be regarded as a set of independent harmonics, what is usually a case in the Fourier transform. The recently proposed SST method [9] permits for providing a time–frequency representation with much more precise frequency and time resolutions at the same time. The above mentioned concept is based first on an identification of the frequencies $f(a,t)$ for which the phase of the wavelet coefficient grows for each scale and time:

$$f(a,t) = \frac{1}{2\pi} \frac{\delta}{\delta t} \arg\left(W_s(a,t)\right), \tag{5}$$

where $\arg(\cdot)$ stands for the phase of the complex coefficient and the multiplier $1/2\pi$ is necessary to convert from circular to the normal frequency. Once the $f(a,t)$ have been determined from the analyzed signal, the frequencies f_i could be chosen to form the bins as $[f_i^-, f_i^+]$ and the SST can be calculated as

$$T_s(f_i,t) = C_{\psi}^{-1} \sum_{j: f_i^- < f(a_j,t) \leq f_i^+} W_s(a_j,t) a_j^{-3/2} \Delta a_j, \tag{6}$$

where Δa_j are the distances between the adjacent scales. The constant C_{ψ} having meaning of amplitude is defined as

$$C_{\psi} = \frac{1}{2} \int_{0}^{\infty} \overline{\Psi(\xi)} \frac{d\xi}{\xi} \tag{7}$$

with $\Psi(\xi)$ being here again Fourier transform of the chosen Morlet wavelet transform in the implementation discussed in this paper. The single channel EEG responses after transformation to the SST frequency domain as in equation (6) are bandpass filtered only in the frequency range of SSVEP stimulation, which allows us to focus only the target oscillations caused by the steady–state stimulus. The original EEG signal could be reconstructed from SST to its time domain form simply [9] as

$$\begin{aligned} s(t) &= \text{real}\left(\sum_i T_s(f_i,t)\right) \\ &= \left|\sum_i T_s(f_i,t)\right| \cos\left(\arg \sum_i T_s(f_i,t)\right). \end{aligned} \tag{8}$$

The very fast implementation of the SST transform and its inverse as in equations (6) and (8) allows for the very precise bandpass filtering of the non–stationary and non–linear EEG. Next the filtered SSVEP responses were transformed into a template brain model using the three–dimensional brain sources reconstruction method as implemented in SPM12 [21]. Only the two highest power spatial brain source partial and limbic locations, as depicted with red color circles in Figure 2, were sonified in the presented project with ambisonics sound spatialization method as described in the next section.

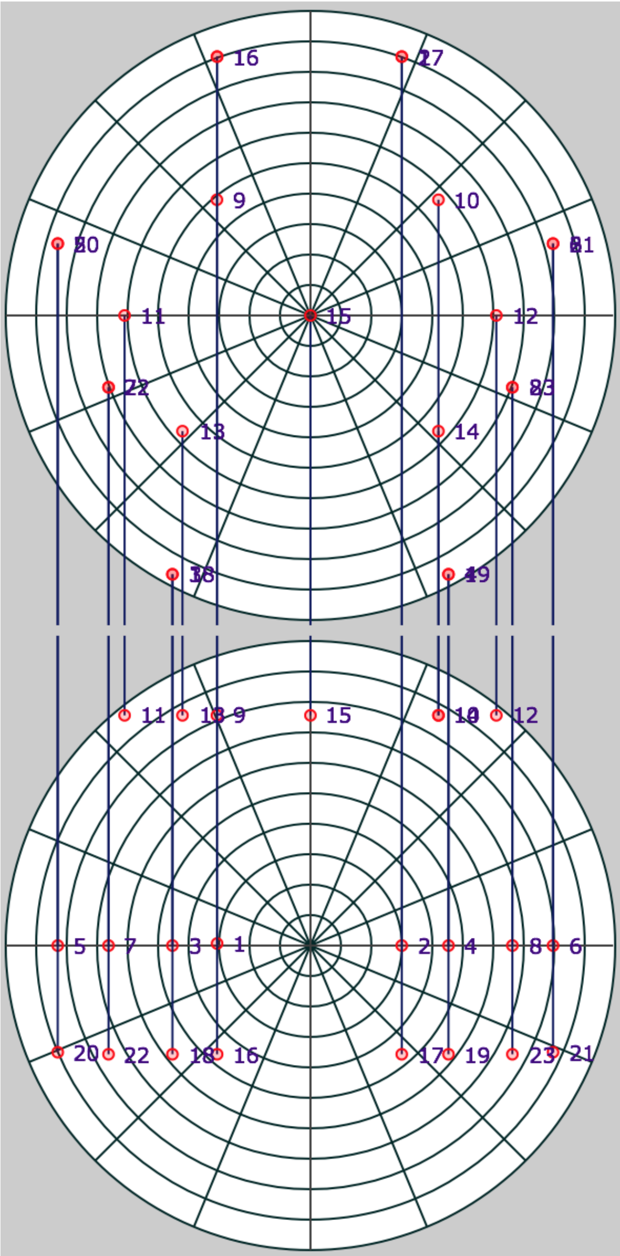

Fig. 1. The three–dimensional acoustic field created with 23 loudspeakers used in this paper with the ambisonics method. The upper circular panel depicts horizontal distribution of the loudspeakers, while the bottom panel vertical plane projection. The figure was created from Ambisonics Externals for MAX/MSP [13] user interface.

B. *Ambisonics*

Ambisonics is a full–sphere surround sound reproduction method for rendering three–dimensional acoustic fields [12]. For the encoding step, the synthesized sound and the space information require a specific loudspeaker set–up (23 loudspeakers system in this paper as depicted in Figure 1).

The method adopts to use an arbitrary setting of several independent channels in order to achieve a desired degree of accuracy. The accuracy is given by the so–called order of the ambisonic. Moreover, the ambisonics panning [12] (positioning of a monophonic sources within a stereophonic image) functions affect all the loudspeakers in the system. The sum of all the loudspeaker gains equals to one.

Locations of 23 loudspeakers used in the presented study are depicted in Figure 1. A full sphere setup was used with eight loudspeakers positioned horizontally at the user's ear level. The additional 15 loudspeakers were distributed over and below the head of the user as shown on lower sphere graph in Figure 1.

In the ambisonics method in order to generate a sound signal for a certain loudspeaker at position

$$P_s = (x_s, y_s, z_s) \tag{9}$$

of a sound image reproduced at another position

$$P = (x, y, z) \tag{10}$$

we multiply it by a transfer function $f(\theta, p)$ where θ denotes an angle between the sound image source (P) and the loudspeaker (P_s). In case of the sphere–shaped loudspeaker setup with a normalized radius of an unity and the sound image of distance r from the center we can calculate the transfer function as [12],

$$f(\theta, p) = \left(\frac{xx_s + yy_s + zz_s + r}{2r}\right)^p, \tag{11}$$

where p denotes the *ambisonic's* order.

The EEG signals were recorded previously in RIKEN Brain Science Institute, Wako-shi, Japan, under their ethical committee agreement and only processed offline in the current study. The modeled brain sources three–dimensional location coordinates (x, y, z) obtained in the previous section were entered into ambisonics equation (11) recreating the spherical sound field (modeling brain space in acoustic modality) as depicted in Figure 1.

The sonification listening experiments were conducted with healthy users, who voluntarily agreed to take a part. All the listening experimental sessions were conducted in the Life Science Center of TARA, University of Tsukuba, Japan. The experiments were conducted in accordance with *The World Medical Association Declaration of Helsinki - Ethical Principles for Medical Research Involving Human Subjects*. The experimental procedures were approved and designed in agreement with the ethical committee guidelines of the Faculty of Engineering, Information and Systems at University of Tsukuba, Tsukuba, Japan (experimental permission no. $2013R7$). The offline SSVEP recordings were sonified in order to visualize in auditory modality the brain processing locations of the steady–state responses. The listeners evaluating the sonified and spatialized sound sources were able to identify the modeled brain source locations (see Figure 2) in the ambisonics recreated sound field.

III. Conclusions

We presented the fully spatial sound SSVEP brainwave response sonification method utilizing the novel SST based

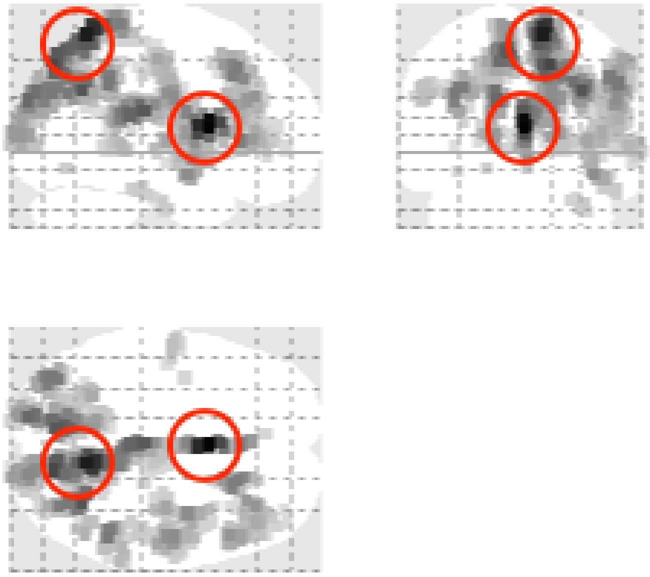

Fig. 2. The brain source reconstructed activity locations as obtained with three–dimensional brain sources reconstruction method [21]. Only the two "red circle" depicted sources in parietal and limbic brain areas (as shown in each of the presented model brain cross–sections) where sonified for the experimental simplicity in the presented approach.

EEG signals adaptive filtering, the three–dimensional brain sources reconstruction technique and the final spatial auditory spatialization with ambisonics approach.

The obtained very encouraging results are a step forward in the novel multivariate signal analysis and visualization methods' development.

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