A REVIEW OF REAL-TIME EEG SONIFICATION RESEARCH

A. Väljamäe*
St. Petersburg State University
Dep. of Higher Nervous Activity
Laboratory of psychophysiology
Universitskaya Nab. 7/9, 199034,
St. Petersburg, Russia

T. Steffert, S. Holland
The Open University
Centre for Research in Computing
Music Computer Lab
Milton Keynes, MK76AA UK

X. Marimon, R. Benitez
Universitat Politècnica de Catalunya
BarcelonaTECH, LASSIE Lab
Automatic Control Department
Comte Urgell 187, 08036
Barcelona, Spain

S. Mealla, A. Oliveira, S. Jordà
University of Pompeu Fabra
DTIC
Music Technology Group (MTG)
Roc Boronat 138, 08018
Barcelona, Spain

ABSTRACT

Over the last few decades there has been steady growth in research that addresses the real-time sonification of electroencephalographic (EEG) data. Diverse application areas include medical data screening, Brain Computer Interfaces (BCI), neurofeedback, affective computing and applications in the arts. The present paper presents an overview and critical review of the principal research to date in EEG data sonification. Firstly, we identify several sub-domains of real-time EEG sonification and discuss their diverse approaches and goals. Secondly, we describe our search and inclusion criteria, and then present a synoptic summary table spanning over fifty different research projects or published research findings. Thirdly, we analyze sonification approaches to the various EEG data dimensions such as time-frequency filtering, signal level, location, before going on to consider higher order EEG features. Finally, we discuss future application domains which may benefit from new capabilities in the real-time sonification of EEG data. We believe that the present critical review may help to reduce research fragmentation and may aid future collaboration in this emerging multidisciplinary area.

1. INTRODUCTION

Recent developments in wearable computing and wireless low-cost physiological sensors have brought brain activity monitoring out of the lab. Many such systems are now commercially available (e.g. NeuroSky [1], Enobio [2], Emotiv [3] and Nexus [4]). Progress in these areas has been accompanied by equally swift developments in auditory hardware, signal processing techniques and wearable audio capability. These joint developments make practical several new approaches for exploiting the real-time representation of brain activity using sound.. The sonification opportunities created in this way promise new applications in several areas; pervasive medicine and health monitoring, neuro- and biofeedback, neuromarketing and implicit interaction interfaces, as well as in other domains that involve the real-time sensing of users perceptual, emotional and cognitive states. Sound-based monitoring and feedback of physiological data have clear advantages in these areas. Indeed, in many respects human auditory perception provides the highest temporal resolution among the sensory modalities. Additionally, in many cases the non-visual information channel is more suitable for wearable applications.

The idea of making electroencephalographic (EEG) signals audible accompanied brain imaging development from the very first steps in the early 1930s. For example, Prof. Edgar Adrian listened to his own EEG signal while replicating Hans Bergers experiments [5]. Indeed, sonification appears to be well-suited for applications based on real-time EEG, since sound can readily represent the complexity and fast temporal dynamics of brain signals. Since the 1930s, a number of scholars and media artists have been experimenting with converting EEG activity into sound. Unfortunately, many of these studies have used rather arbitrary conversions of EEG data into sound. In addition, the associated publications often do not provide sufficient details about either physiological data acquisition or applied sound synthesis. Very few of these studies have conducted any kind of controlled evaluation of their chosen methods, making it impossible to replicate or validate most studies. Given these widespread limitations, a critical review of the current state of this emerging multidisciplinary field may help to facilitate its future healthy development.

The present paper presents an overview and critical review of EEG data sonification research. We first present a synoptic summary table spanning over fifty different research projects or published research findings (20% of these are works from ICAD proceedings). This is followed by the analysis of sonification approaches to the various EEG data dimensions such as time-frequency filtering, signal amplitude, location, before going on to consider higher order EEG features. This then allows us to address several wider questions, namely:

- What application domains have employed real-time EEG sonifications?
- What sonification techniques have been applied to real-time EEG sonification?
- What EEG features have been sonified in real-time, and with what temporal resolutions?
- What experimental, methodological and validation techniques have been used in real-time EEG sonification?

2. MAIN APPLICATIONS AREAS OF EEG SONIFICATION

Leaving aside the real-time constraint, there are diverse application areas that use EEG sonification, but for quite different reasons. Six distinct applications areas can be differentiated in terms of their use of data (real-time or off-line), and on a continuum between functional and aesthetic as shown in Fig. 1.

Within specifically real-time EEG sonification, several main application areas can be identified based on their objectives, and on validation methods used in the studies. Firstly, real-time EEG *monitoring* designed to inform a third person about the user state,

* Corresponding author, Also with Department of Behavioural Sciences and Learning, Linköping University, Linköping, Sweden. *E-mail address*: aleksander.valjamae@gmail.com.

e.g. an anaesthetist during surgery [6], or to inform the user herself, e.g. an air traffic controller being warned of her critical fatigue level. A second related, though strictly off-line sonification of EEG is done for *diagnostic* purposes where brain imaging data is speeded up, usually by a factor of 50-200 times to allow fast identification of prominent changes, e.g. different sleep states [7], or epileptic seizures [8]. Thirdly, *neurofeedback* applications target learning about a users own brain state and, importantly, aim at altering this state, e.g. for post-stroke rehabilitation. The fourth domain concerns sonification that is used for *Brain Computer Interface feedback and communication*. For example, sound has been successfully used for training the strength of brain activity in left vs. right motor imagery in order to control external hardware [9, 10]. As a special case of this domain ,some applications use EEG for creating brain controlled *musical instruments* [11]. Finally, EEG patterns can be directly converted to music. Miranda and colleagues work on BCMI technology that makes it possible to detect specific brain patterns and turn them directly into *musical compositions* [12, 13].

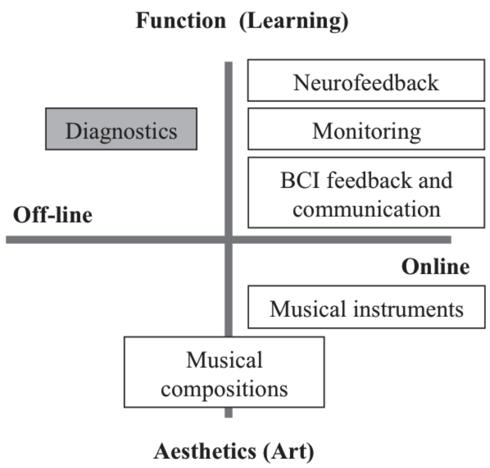

Figure 1: Application areas that use EEG sonification. Applications areas can be distinguished in terms of EEG data processing (real-time or off-line), and on a continuum between functional and aesthetic. Diagnostics applications are not addressed in this review.

All of these application domains have different objectives, different constraints and different validation methods. One of the dimensions that helps to differentiate between sonification approaches is to contrast ways in which one would expect the end results to be judged, for example quantitative vs qualitative judgement. With Miranda's BCMI, just listening to the sonification may be sufficient for demonstrating that the system works. With BCI based musical instruments like in [11], the player can judge the extent to which the interface allows the musically necessary degree of control. But both of these domains are more concerned with the aesthetics of the resulting sonic composition than any other kind of validation. The situation is very different for diagnostic and neurofeedback uses of real-time EEG sonification, where the informational and perceptual value of produced sounds is of primary importance and determines the functionality of the application.

3. SEARCH AND SELECTION CRITERIA

To get an overview of the range of published works we searched a number of databases including Web of Science, Pubmed and Google Scholar. The search terms included *sonification, audio, sound, auditory display, EEG, neurofeedback, biofeedback*. One can observe a clear trend of growing activity in EEG sonification. For example, when searching Google Scholar using *"sonification + EEG"*, only 25 publications are returned for 2002 but already 140 for 2012. Unfortunately, these publications often do not always adhere to a highest scientific standard and in some cases represent ongoing work in progress. Furthermore, approximately 70% are conference publications that are often not peer-reviewed. We decided to report on the majority of publications found, by applying the following selection criteria.

Our first selection criterion was the use of sonification in selected works. Immediately, the issue of definition arises. According to ICAD, sonification is *"the use of non-speech audio to convey information; more specifically sonification is the transformation of data relations into perceived relations in an acoustic signal for the purposes of facilitating communication or interpretation"* [14]. However, we followed Hermann's four conditions for sonification [15]. This author gives a broader definition of sonification than has been traditionally usual in the field as *"a technique that uses data as input, and generates sound signals (eventually in response to optional additional excitation or triggering)"*. This definition includes also auditory icons and earcons that can be used to represent the discrete events of the brain imaging data using ecological or symbolic sounds.

Some of the work on conversion of EEG data into sound that we also included does not strictly correspond to the above definitions. A good example is Brain-Computer Interfaces (BCI) based on evoked-potentials techniques whose output is sound or music [16, 17]. Nevertheless, we decided to include them because of their real-time approach and possible compatibility with other sonification approaches. Another special case are Brain-Computer Music Interfaces (BCMIs) by Miranda and colleagues [12, 13], that do not strictly satisfy sonification criteria but use various BCI control techniques in order to produce meaningful musical outcomes. However, auditory BCI that has been used in speech applications has been omitted here (see [18] for the full list of auditory and multisensory BCI's).

Our second selection criteria was the possibility of using sonification in real-time. Some papers found dealt with sonification of pre-recorded time compressed EEG data with the purpose of prescreening specific events, e.g. when detecting the epileptic seizures and seizure lateralization [8] or listening to different sleep stages [7]. These works were not included in the tables and Fig. 2 below. However, we included the works that did off-line analyses that could potentially lead to on-line sonifications at the later stage.

We did not include papers in our review that would deal with other types of brain imaging like fMRI [19, 20] or ECoG [21]. Where journal papers revisited the same ground covered by earlier conference publications, the journal publications was used rather than the conference paper. In cases where the overlap was only partial, some results and methods ended up with two or more entries in our database. In such cases multiple publications were used as sources, but only counted as one in our statistics and table entries. Finally, due some difficulties in reaching originals of older artistic works that used EEG sonification, we did not include these (interested reader can see an insightful monograph by one of the pioneers of EEG sonification, David Rosenboom [22] and references therein).

4. RELATING EEG DATA PROCESSING TO SONIFICATION CATEGORIES

The first visual overview of the EEG sonification research reviewed is given in Fig. 2 where the X-axis corresponds to *Sound Generation* strategies and Z-axis to *Data Processing* techniques. Within these two dimensions, all selected publications were classified into one or more of these categories (i.e. a single article may cover more than one sonification technique and/or data processing strategy).

4.1. Sonification techniques

Following proposed revisions in the terminology of sonification, we based the first three categories of sonification techniques on Herman's [15] and deCampo's definitions [23]: *audification, parameter mapping* and *model-based approaches* based on continuous or discrete events. The last category of *generative music* is added to include the BCMI works.

Audification represents the simplest and oldest approach to sonification (e.g. [5]). In this technique, variations in EEG data values are directly treated as a soundwave. It is often applied when off-line EEG data is time-compressed by a factor of 50-200, shifting EEG frequencies to audible spectra. This offline approach is excluded from Fig. 2. Besides very old works, none of the papers we reviewed have being doing audification and one can say that this approach is largely obsolete.

[1]***Parameter mapping*** is currently the broadest and most popular form of sonifying the EEG signal. The simplest example would be mapping activity in an EEG alpha band to an intensity level of a sound. This technique encompasses many mapping methods as described by [24] and [23] (e.g. *Continuous, Event-based, or Spectral mappings; Distance Matrix method; Induced Waves/Spikes; Judging Correlation; Vocal Sonification etc.*).

In [2]***Model-Based Sonification*** the approach relies on mathematical models that generate sound according to the EEG data input. For example, a sound synthesis model for a bell sound might be changed by the amplitude of the alpha rhythm. This has an analogy to real-world sound generating phenomena. For example, one could shake a black box to find out what is inside by means of the sound it produces. This indirect sonification approach has been gaining increasing attention over the last decades due its suitability for using different data sets as an input [25, 26].

[3]***Generative music*** is a very broad term that is used in many different contexts. Here it describe systems that use musical rules and structures to create sound output using EEG data as a control signal. For example, BCMI works of Miranda and colleagues [12, 27], but also other performance oriented works that are mainly concerned with output music expressiveness [28, 29, 30].

4.2. Data processing strategies

To classify the various studies, we chose data processing bins according to the most used methods, which we grouped into eight data processing categories (Z-axis). The superscript **from 1 to 3** indicates the correspondence of each publication to one of the four sonification categories described above. The data processing bins are as follows.

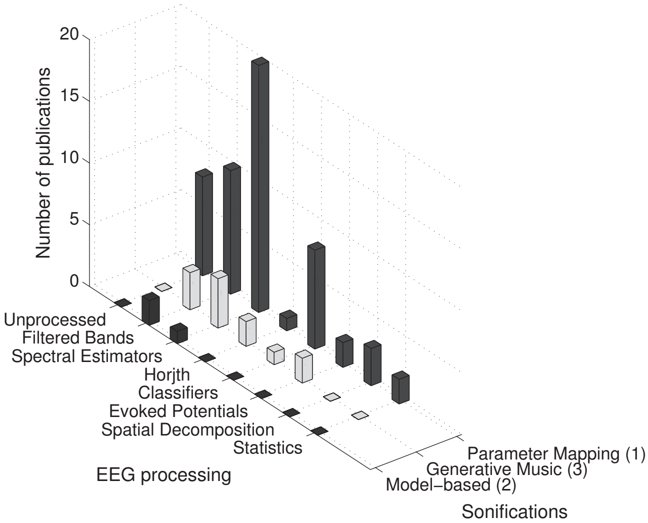

Figure 2: Data Processing vs. Sonification techniques. This figure shows several trends. Simple processing of EEG data has been gaining in popularity. Remarkably, only for the *Filtered Bands* and *Spectral Estimators* processing categories have all three sonification techniques been applied. Among different frequency bands alpha and beta activities have been the most sonified. Interestingly, many works that applied more complex processing such as classifiers tended to use more simple sonifications based on parameter mapping, while most of the EEG-based music approaches used more traditional and simple signal processing methods. This may illustrate a difference between computer science and computer music communities, reflecting their different purposes.

In the ***Unprocessed*** category we place sonifications that use the raw EEG signal and its features, such as: registered zero-crossings [1][31]; max/min voltage [1][32, 33, 34, 35]; [1][33, 34, 36, 37, 31, 38]; temporal aspects of max/min voltage change [1][33, 34]; inter-maxima and minima values [1][32]; period [1][33, 34, 36, 38]; voltage threshold values [1][33, 34].

The second processing category, ***Filtered Bands***, refers to sonification of EEG signal filtered in time domain for the following bands: Delta [1][39, 40, 41, 42, 43, 24, 44], [2][39], [3][12, 45]; Theta [1][39, 40, 41, 42, 43, 24, 46], [2][39], [3][12, 45]; Alpha [1][47, 46, 40, 11, 41, 42, 48, 24, 39, 43, 9], [2][26], [3][49, 29, 28]; Beta [1][47, 39, 9, 40, 11, 41, 42, 24, 39, 50], [2][26], [3][49, 29]; Gamma [1][40], [2][26]; Mu rhythm [1][11, 40, 41], Slow Cortical Potentials (SCP) [1][43];

The third processing category of ***Spectral Estimators*** applies to block-wise frequency conversion using FFT or other transforms in order to estimate the following EEG features: energy [1][51, 52, 53, 37, 40, 41, 54]; [2][26]; [3][55] power [1][11, 27, 56, 47, 42, 36, 31, 38, 39]; [3][55, 12, 27, 45]; power ratios including Index of Symmetry (SI), Assymetry Ratio or Affective states estimation[1][57, 58, 11, 27, 56, 37, 59, 60, 41]; autocorrelation [1][32, 33, 34]; and crosscorrelation [1][32, 39].

The forth category ***Hjorth's parameters*** lists papers that used this signal complexity measure: [1][32] and [3][12, 45] .

The fifth category concerns miscellaneous ***Classifiers*** including Linear Discriminant Analysis (LDA) **1**[52, 10], Principal Component Analysis (PCA) **1**[61], Independent Component Analysis (ICA) **1**[16, 62, 63] or artificial neural networks **1**[11, 27, 52, 10], **3**[64].

A few papers in sixth category concerned ***Evoked potentials*** based sound production **1**[16, 17], and generative music **3**[30, 13].

The seventh category ***Spatial Decomposition*** includes Common Spatial Patterns (CSP) **1**[11, 10], and Common Spatial Subspace Decomposition (CSSD) **1**[27].

Finally, some sonifications used ***Statistical Analysis*** based features such as like Spectral Entropy **1**[56] and Gaussian Kernel **1**[25].

5. EEG PROCESSING DIMENSIONS

To have a closer look at the sonification techniques used by different authors, we selected a number of EEG signal dimensions that were described by authors when converting brain imaging data into sound: time-frequency parameters, signal level, recording sights and high-level processing techniques.

5.1. Time-frequency dimension

One aspect of EEG processing to consider is to see how its temporal aspects are addressed, particularly any latencies introduced. The simplest and most straight-forward sonification technique is the direct conversion of *instantaneous values* of EEG signals to sound. This approach is known as *audification* and despite being vulnerable to signal transients, it can be useful for tasks such as locating outliers or detecting repeating patterns [24]. In this case, latencies are minimal, and where present are mostly caused by hardware limitations. A sliding window technique is often used to smooth the data, e.g. to reduce muscle artefacts, by computing a *moving average*. This windowing approach introduces some delay caused by the size of the window (with typical window sizes are varying between 50 ms and several seconds).

Table 1: Time-frequency based features in EEG sonification

Features	*Description and associated papers*
Instantaneous signal values	Audification and event/feature extraction: [11, 32, 34, 41, 40, 27, 24, 39, 35, 25, 50, 43, 44, 48, 59, 12, 49, 65, 16, 62, 63, 31, 29, 28].
Time domain	Signal filtering in temporal domain: [11, 51, 60, 24, 39, 43, 44, 48, 16].
Frequency domain	Signal filtering using block-based conversion into frequency domain: [33, 41, 40, 27, 56, 26, 39, 43, 44, 48, 47, 30, 42, 46, 12, 49, 13, 16, 45, 54, 36, 38, 52, 10, 55, 57, 58].
Running window	Using moving average for smoothing and/or artifact removal (eye-blinking, muscular movements, etc): [11, 32, 41, 40, 51, 56, 61, 35, 25, 50, 44, 48, 59, 12, 13, 45, 62, 63, 37].
Latency times	Latency caused by signal buffering: [11, 32, 41, 40, 51, 56, 50, 48, 45, 62, 63, 37, 17].

Another source of delay is signal filtering. Time domain based approaches use finite or infinite impulse response filters to look at the signal in specific frequency bands. Frequency domain approaches use *windowing* and block-based strategies to select a number of samples to convert into a frequency domain, typically by means of FFT. In such systems, window size determines the major source of system delay.

The biggest latencies in EEG sonification appear in event-based sonification approaches where EEG data is buffered till some significant event occurs. Table 1 shows the distribution of publications according to these time-frequency features. Please note that the list of works that use wavelet transforms is given in Table 6, as typically these transforms are used as a first stage of higher order EEG processing.

Several trends are apparent from comparing the listed works. Firstly, the most popular technique for filtering is a block-based (typically FFT) conversion of the time signal into the frequency domain. This approach inevitably leads to latency in the system reflecting the used window size. Several works deliberately increase this since their sonification strategies are based on musical structures and event-based mappings. Secondly, a considerable number of works (25) still rely on straightforward sonification of instantaneous values with the objective of detecting outliers or periodical patterns of EEG data. Many artistic works that do not apply heavy signal processing and rely mostly on audification also fall into this category.

System latency is perhaps the most under reported but critical issue for many applications, for example, for neurofeedback. Any delay in the feedback will reduce the contingency of the sound signal to the brain activity and greatly increase learning times in neurofeedback training. In real-time EEG visualization, it is common to apply some averaging to the signal in order to reduce any eye strain caused by the rapid flicker of the display, but this is often done without any appreciation of the detrimental consequences. Given the excellent temporal resolution of both sonification and EEG, this is probably a key advantage of real-time EEG sonification over visualization techniques.

The works using transform- or filtering-based conversion to frequency domain are depicted in Table 1. The majority of these works sonify certain frequency power or energy as described in next section and Table 2. It should be noted, however, that a few works use frequency domain conversion to trace spectral dynamics of EEG and use shifts of a certain frequency or a certain band maximum frequency as features to be sonified [9, 24, 48, 37].

5.2. Level-based dimension

The level of amplitude of EEG is one of the most fundamental properties of the signal and reflects the firing rate of the neurons, which in turn mirrors the activation level of the underlying area of the brain and its information processing. A fast and accurate representation of this parameter is critical in estimating the rapid fluctuation of the underlying cognitive states of the user. In both neurofeedback and EEG monitoring the level of particular sets of parameters is of primary interest, e.g. frontal alpha power reflecting the alertness of the user.

Table 2 summarizes EEG sonification papers based on their treatment of various scalar features of the EEG signal, both in temporal and frequency domains. As it can be seen, EEG power is the most used parameter for sonification. The second most used parameter is voltage amplitude. Surprisingly, relative power (i.e relative amplitude), which is commonly used in EEG fields like neurology or neurofeedback, is rarely used in sonifications. One possible reason for this concerns the availability of baseline levels in the two contexts.

In experimental settings, baseline levels, e.g. rest conditions, are routinely available to normalize the data for later comparison across users or sessions. By contrast, in real-time sonification sessions, baseline recordings are rarely available. Ideally, both relative and absolute level values should be monitored. Because of the complexity and constant activity of the brain, there is always a high level of background noise to contend with when inferring activation of a particular area or network of the brain, e.g. onset of epileptic attack [33, 34]. One of the main methods for addressing this issue is to detect extreme values, maxima values and link these to sonification events. Another method, commonly used in neurofeedback, is to detect when the parameter exceeds some threshold or zero-crossing value. In this case, threshold selection is dependent on the application and can be critical for its success.

Table 2: Signal level based features in EEG sonification

Features	*Description and associated publications*
Extremal values (max/min)	Instantaneous detection of signal's peak maximum and minimum EEG signal: [32, 33, 34].
Voltage Amplitude	Amplitude of the EEG signal: [43, 48, 38, 31, 37, 36, 55, 33, 34, 50].
Zero-crossings	Detection of events (EEG waves) based on zero-crossing: [31].
Thres-holding	Detection of EEG events by signal thresholding: [33, 34].
Energy	Absolute spectral amplitude of frequency transformed signal: [53, 37, 51, 52, 41, 26, 24, 44, 46].
Power	Squared absolute spectral energy of frequency transformed signal: [11, 27, 56, 42, 39, 12, 13, 36, 31, 38, 45, 47, 42, 9, 28, 49, 57, 58, 59].
Relative Power	Power of a specific frequency band with respect global EEG power spectrum: [60].

5.3. Location based dimension

The brain has specialized regions for different tasks with the sensorimotor cortex being the most prominent for BCI and neurofeedback applications. However, many mental operations rely on networks of neurons working in concert. Therefore, despite the relatively poor spatial resolution of EEG, the location of electrodes is an important factor for measuring a specific cognitive operation. Furthermore usage of multiple electrodes allows detecting the neuronal activity from specific networks, permitting a number of space related features for sonification.

Table 3 shows the distribution of papers regarding their use of multi-channel EEG systems. Most of the reviewed works use up to 20 EEG channels, with a smaller group of authors working with higher spatial resolution. The systems that used more than 32 channels are quite recent and it reflects the growing use of EEG multi-channel systems. The amount of channels used reflects the type of application. While practical systems at clinics tend to have fewer channels, research and diagnostic applications tend to use more channels. Many high-order statistical methods for brain activity localization, like ICA and LORETA (see next section), require a minimal set of channels of approximately twenty.

A few works currently use recording site location on the head as a parameter for sonification (Table 4). Spatialization and panning are now the most common mappings, mostly designed to display sound according to the hemispheric locations of the brain activity. Interestingly, there are a number of works emerging that make use of channel correlation as an input to sonification parameters, such as timbre or pitch. This trend is likely to increase once higher numbers of multi-channel systems are in use.

Table 3: Number of channels used in EEG sonifications

# of Ch.	*Description and associated papers*
Channels $\leq$10	Sonification systems using up to 10 EEG channels: [66, 40, 47, 42, 38, 28, 10, 46, 65, 31].
Channels 11-20	Sonification systems using between 11 and 20 EEG channels: [11, 60, 27, 56, 24, 59, 12, 53, 58].
Channels 21-32	Sonification systems using between 21 and 32 EEG channels: [39, 35, 65, 36].
Channels 33-64	Sonification systems using between 33 and 64 EEG channels: [42].
Channels 65-128	Sonification systems using between 65 and 128 EEG channels: [65].
Channels # not defined	Sonification systems that do not specify a number of channels used: [26, 25, 61, 50, 43, 48, 59, 29, 65, 13, 16, 45, 62].

Table 4: Location as a feature in EEG sonifications

Features	*Description and associated papers*
Hemisphere discrimination	Sonification systems that apply left/right panning according to electrodes' hemispheric location: [11, 32, 40, 56, 24, 39, 9, 10].
Location/ Spatialization	Sonification systems that use spatial sound according to electrodes' location: [11, 32, 33, 34, 24, 35, 50, 59].
Location/ Correlation	Sonification systems whose auditory display strategies are based on correlations between EEG channels: [32, 24, 57, 65].
Location/ Sound features	Sonification systems that use timbre or pitch transformation to represent different electrodes' location: [24, 39].

Table 5: Electrode montage in EEG sonifications

Montage	*Description and associated papers*
10-20 system	Sonification systems using the 10-20 placement system: [11, 32, 33, 34, 40, 60, 56, 27, 24, 39, 43, 48, 43, 59, 57, 47, 38, 10, 46, 12, 65, 64, 53, 62, 31].
Custom montage	Sonification systems using custom electrode placement: [66, 33, 34, 40, 65].
Placement not defined	Sonification systems that do not specify used electrode montage: [26, 25, 61, 35, 50, 29, 42, 28, 37, 45, 16, 42, 13].

Details of electrodes location depend on their placement or, in other words, montage (Table 5). Using standard electrode placements gives the possibility for replication of sonifications. Table 5 shows that the so called 10-20 system [67] proved to be the most commonly used in the reviewed works, with a few specific exceptions that made use of custom placement methods, mostly due to hardware design (i.e. do-it-yourself devices or commercial low-cost headsets). Surprisingly, a considerable number of publications (around 40%) neither specified placement system nor EEG sensor positions that were used for sonification.

5.4. Features based on higher level processing of EEG

A number of sonifications made use of some computational techniques before converting data into sound. Indeed, it seems that any real indices of human brain activity that can represent some cognitive, emotional or perceptual processes are likely to come from higher order processing of EEG data. An intermediate step towards this goal is to use higher-order processing of EEG to represent different brain regions activity. For example, consider biologically inspired method of *bump sonification* method by Cichocki and colleagues [62, 54] that tries to reveal time-frequency structure (oscillatory patterns) of brain activity.

Table 6: High-level processing of EEG data

Processing	*Description and associated papers*
LDA	Linear Discriminant Analysis. Classifier based on quadratic distance in the feature space: [52].
PCA	Principal Component Analysis. Orthogonal features based on statistical correlations between signals: [61].
ICA	Independent Component Analysis. Features based on statistical independence between signals: [16, 62, 63].
Neuronal Networks	Classification using artificial neural networks: [11, 27, 52, 64].
CSP	Common Spatial Patterns: [11, 27, 52].
CSSD	Common Spatial Subspace Decomposition: [11, 52].
Spectral Entropy	Descriptor of the information content of the EEG signal: [56].
Gaussian kernel	Classification kernel based on a normal distribution: [25].
Evoked potentials	The P300 component based synchronous BCI system in [17] and Steady-State Visually Evoked Potentials in [16, 30, 13].
Time-Frequency	Obtained using the short-time Fourier transform or distribution functions: [16].
Wavelets	Use of wavelets to filter the signal and to obtain time-frequency characterisation: [11, 16, 62, 63, 54, 37, 27].
Hjorth	Calculation of time-varying Hjorth parameters: [32, 12].
Affective state	Tries to estimate the levels of intensity and valence degree (positive or negative) of an emotional response: [57, 37, 58]

Many of higher-order processing techniques depend on multiple electrode systems, and might be more widely applied in the future. Unfortunately, many of the computational techniques used in EEG analysis are still not well suited for real-time applications. Table 6 below demonstrates the divergence in tool sets used by different research groups.

Hjorth and wavelet based analysis are most commonly used among the presented techniques. However, it should be noted that it is still a small number of works (< 10 for each processing method) compared to more simple power band sonification approaches reviewed in Fig. 2. The Hjorth's EEG descriptors are mainly used in BCMI works.

A recent and promising trend is to sonify affective states of the users. Since processing basic acoustic features is closely linked to emotional responses (e.g. rising/falling intensity influences on emotional processing [68]), real-time emotional state sonifications can be directly applied both for emotion regulation and for basic research on affective chronometry. However, more clear and well grounded indices of emotional processing should be first established before useful sonification approaches can be explored.

6. CAVEATS AND FUTURE WORK SUGGESTIONS

A literature review of this kind presents certain difficulties. Firstly, there is a lack of common terminology due to the large level of multidisciplinarity in the field of EEG sonifications. For example, an insightful paper from a specialist in the anesthesia domain recently introduced the term *Audio EEG* without mentioning sonification or auditory display works [6]. Secondly, many papers lack technical details on the sonifications used, the EEG recording equipment and the processing techniques. A few papers may serve as an example of good methodology reporting practice, e.g. [34, 40, 44, 25, 37].

There are many factors that affect the quality and usefulness of an EEG signal (e.g. [69]). It is important to note how well the electrodes are placed and the quality of all of the components in the acquisition system, from the gel and the electrodes used to the amplifier and even the environment in which data is recorded. One of the main difficulties in using EEG is the prevalence of artifacts: from eye blinks and muscle movement to loose or bad electrodes. Unfortunately, the frequency spectrum of electromyogram (EMG) overlaps significantly with that of EEG, so it is not possible to simply filter out the EMG. Sometimes commercially available wearable EEG based systems even use EMG artifacts as an additional control input of their device to compensate for the lack of recorded brain signal quality. Common practice when using real-time EEG is to have a display of the raw EEG signal in order to check for movement artifacts and bad electrode contacts, even if the main interest is a filtered band or a relation between sub-components of the EEG. Interestingly, sonification of movement artifacts could serve an important aid for the user to identify and minimise these artifacts.

Future papers addressing the topic of EEG sonification, in any of the application domains, would benefit from providing more documentation on the EEG methodology and sonfications used. EEG recording methodology description should include:

- equipment used (amplifier models, electrodes),
- electrode placement, channels used and referencing technique
- EEG sampling rate,
- applied low and high pass pre-filtering,
- signal processing details (e.g., FFT block size),
- artefacts reduction.

Sonification methodology descriptions, in line with Hermann's conditions for sonification [15], should include:

- which EEG features (objective properties or relations) are being sonified; for example, signal level, temporal, spectral and spatial patterns,
- what sonic and/or musical parameters are used for transforming/generating the auditory contents, and what are the precise mappings established between these parameters and the extracted EEG features.

Finally, almost none of the works have done proper validation of their sonification methods (but see, e.g. [70]). In other words, we still do not know what types of sonification are most efficient for representation of EEG data for particular purposes. Of course, these validation metrics may differ depending on the application in question. With BCMI applications, just listening to sonifications may be sufficient for demonstrating that the system works. With Arslan's musical instruments the player would know whether or not the correct notes were selected [11]. At the same time, both diagnostic and neurofeedback applications need much more rigorous assessment (randomised and double blind control studies) to persuade the medical community of the worth of sonification. The lack of qualitative assessment may simply reflect the early stage of development of the research field. Hopefully, in the future there will be more studies comparing different sonifications with proper control methodologies.

7. FUTURE OUTLOOK

It is clear that a number of domains like BCI, polysomnography or neurofeedback could directly benefit from better EEG data information displays. Here, the emergence of solid physiology-based commercial applications, e.g. BCI-based gaming, will greatly facilitate the further development of EEG sonification field. The widespread use of hand-held devices with visual displays of limited size will bring more attention to sound as an information channel. Moreover, in some activities such as driving or surgery, visual input can not be overloaded. Additionally, the sophistication and growing availability of wearable physiology sensing devices (and, potentially, implants) will call for improved feedback technology for data display. In this situation sonification has promise as an alternative or a complement to visualisation delivered via techniques such as augmented reality displays [71]. Here, bone-conducted sound (e.g., [72]) can be an interesting alternative for neurofeedback and monitoring applications based on EEG sonification.

Surprisingly, very few EEG sonifications have been augmented by other sensory modalities, such as visualization. Given that our perception is multisensory [73], combining auditory, visual and tactile information is likely to produce enhanced multisensory displays. In addition, increasing the number of possible information channels may help to address the challenge of concurrent sonification of multiple EEG signals, either from a single user or from a group activity such as EEG hyperscanning. However, more studies like [43] are needed to clarify the effectiveness of multisensory feedback (or as one may call it *"multisensualization"* or *perceptualization* as in [74]) comparing it with corresponding unisensory feedback versions before suitable multimodal combinations can be established.

While sonification work can greatly enhance the emerging field of hybrid and multisensory BCI's [18], multimodal tangible systems that are used for physiological data exploration represent another potential area for development of EEG sonification [35]. Recently we created a system that allows users of a tangible interface to sonify their own EEG data streamed directly from the electrode cap [46]. This scenario enriches Hermann's hierarchy of interaction loops in auditory systems [15] representing a combination of interactive sonification and auditory biofeedback. A recent study shows that Brain-Tangible User Interfaces (BTUI) of this kind can be successfully used for studying group collaboration during music creation tasks [75, 76].

There are few studies dedicated to the validation or effectiveness of EEG sonifications. In the " Concert Call for Sonifications" made by Barrass and colleagues in 2006 [70] 27 multichannel sonifications of the same EEG dataset by 38 composers and 88 analytical reviews about these works were collected. This effort serves as a good example of the type of initiative that EEG sonification field would benefit from. Similar competition "Calls" could be made in the future to address EEG sonfication for concrete applications, such as monitoring the depth of anesthesia [6]. Clearly, sonifications evaluation criteria would vary depending on the concrete application. The availability of good quality data sets that are made publicly available might foster sonification competitions similar to ones organized by the BCI community.

To conclude, many works have addressed EEG sonification and it appears that this sub-domain of Auditory Displays is now receiving attention from the research community. However, so far much of the work has been of a "proof-of-concept" type. Hence, the time is now right to build on these initial results and start directly comparing different sonification methods, mapping schemes used and addressing other questions that can lead to a significant impact on the various application areas in the real world.

8. ACKNOWLEDGMENT

The first author of this paper received funding from the People Programme (Marie Curie Actions) of the European Union's Seventh Framework Programme (FP7/2007-2013) under REA GA-303172.

9. REFERENCES

[1] "Neurosky," www.neurosky.com, 31/05/2013.

[2] "Neuroelectrics," www.neuroelectrics.com, 31/05/2013.

[3] "Emotive," www.emotiv.com, accessed: 30/03/2013.

[4] "MindMedia Nexus," www.mindmedia.nl, 31/05/2013.

[5] E. Adrian and B. Matthews, "The Berger rhythm: potential changes from the occipital lobes in man," *Brain*, vol. 57, no. 1, pp. 355–385, Jan. 1934.

[6] J. Glen, "Use of audio signals derived from electroencephalographic recordings as a novel 'depth of anaesthesia' monitor." *Medical hypotheses*, vol. 75, no. 6, pp. 547–9, Dec. 2010.

[7] J. Olivan, B. Kemp, and M. Roessen, "Easy listening to sleep recordings: tools and examples," *Sleep Medicine*, vol. 5, no. 6, pp. 601–603, 2004.

[8] H. Khamis, A. Mohamed, S. Simpson, and A. McEwan, "Detection of temporal lobe seizures and identification of lateralisation from audified EEG." *Clinical Neurophysiology*, vol. 123, no. 9, pp. 1714–20, Sep. 2012.

[9] T. Hinterberger, J. Hill, and N. Birbaumer, "An auditory brain-computer communication device," in *Proc. IEEE BIOCAS'04*, 2004.

[10] K. McCreadie, D. Coyle, and G. Prasad, “Sensorimotor learning with stereo auditory feedback for a brain-computer interface,” *Medical & Biological Engineering & Computing*, vol. 51, no. 3, pp. 285–93, Mar. 2013.

[11] B. Arslan, A. Brouse, J. Castet, J.-j. Filatriau, R. Lehembre, Q. Noirhomme, and C. Simon, “Biologically-driven Musical Instrument,” in *Proc. ENTERFACE’05*, Mons, Belgium, 2005.

[12] E. R. Miranda and A. Brouse, “Interfacing the Brain Directly with Musical Systems: On Developing Systems for Making Music with Brain Signals,” *Leonardo Music Journal*, vol. 38, no. 4, pp. 331–336, 2005.

[13] E. R. Miranda and R. Magee, W., Wilson, J. J., Eaton, J., and Palaniappan, “Brain-Computer Music Interfacing (BCMI): From Basic Research to the Real World of Special Needs,” *Music and Medicine*, 2011.

[14] G. Kramer, B. Walker, T. Bonebright, P. Cook, J. Flowers, N. Miner, and E. Al., “Sonification report: Status of the field and research agenda,” National Science Foundation, Santa Fe, NM, Tech. Rep., 1999.

[15] T. Hermann, “Taxonomy and definitions for sonification and auditory display,” in *Proc. ICAD’08*, 2008.

[16] T. M. Rutkowski, F. Vialatte, A. Cichocki, D. P. Mandic, and A. K. Barros, “Auditory feedback for brain computer interface management - An EEG data sonification approach,” in *Proc. KES’06*, 2006.

[17] B. Hamadicharef, M. Xu, and S. Aditya, “Brain-Computer Interface (BCI) Based Musical Composition,” in *Proc. IEEE CW’10*, 2010.

[18] I. Wagner, I. Daly, and A. Valjamae, “Non-visual and multisensory bci systems: Present and future,” in *Towards Practical Brain-Computer Interfaces*, ser. Biological and Medical Physics, Biomedical Engineering, B. Z. Allison, S. Dunne, R. Leeb, J. Del R. Millan, and A. Nijholt, Eds. Springer Berlin Heidelberg, 2013, pp. 375–393.

[19] G. Weinberg and T. Thatcher, “Interactive Sonification of Neural Activity,” in *Proc. NIME’06, Paris, France*, 2006.

[20] T. Schmele and I. Gomez, “Exploring 3D audio for brain sonification,” in *Proc. ICAD’12*, Atlanta, GA, USA,, 2012.

[21] C. Potes, A. Gunduz, P. Brunner, and G. Schalk, “Dynamics of electrocorticographic (ecog) activity in human temporal and frontal cortical areas during music listening,” *NeuroImage*, vol. 61, no. 4, pp. 841 – 848, 2012.

[22] D. Rosenboom and L. M. Number, “Extended musical interface with the human nervous system,” *LEONARDO MONOGRAPH SERIES International Society for the Arts, Sciences and Technology (ISAST)*, no. 1, 1997.

[23] A. De Campo, “A data sonification design space map,” in *Proc. ISon’07, York, UK*, 2007.

[24] T. Hermann, P. Meinicke., H. Bekel., H. H. Müller., S. Weiss., and R. Helge, “Sonifications for EEG data analysis,” in *Proc. ICAD’02*, Kyoto, Japan, 2002.

[25] T. Hermann, G. Baier, U. Stephani, and R. Helge, “Kernel Regression Mapping For Vocal EEG Sonification,” in *Proc. ICAD’08*, 2008.

[26] Z. Halim, R. Baig, and S. Bashir, “Temporal Patterns Analysis in EEG Data using Sonification,” in *Proc ICIET’07*, 2007.

[27] J. J. Filatriau, Q. Noirhomme, B. Arslan, A. Brouse, J. Castet, C. Simon, and R. Lehembre, “Using physiological signals for sound creation,” in *Proc. SPECOM’06*, St. Petersburg, Russia, 2006.

[28] S. Mann, J. Fung, and A. Garten, “Deconcert : Bathing In The Light , Sound , And Waters Of The Musical Brainbaths,” in *Proc. ICMC’07*, 2007.

[29] B. Karabey, “Clash of the Brainwaves: A Cyber Musical Duet Between a Plant and a Human Being,” *Amber Art Technology Conference*, 2009.

[30] S. L. Groux, J. Manzolli, P. F. M. J. Verschure, M. Sanchez, A. Luvizotto, A. Mura, A. Valjamae, C. Guger, R. Prueckl, and U. Bernardet, “Disembodied and collaborative musical interaction in the multimodal brain orchestra,” in *Proc NIME’10, Sydney, Australia*, 2010.

[31] D. Wu, X. Shi, J. Hu, X. Lei, T. Liu, and D.-Z. Yao, “Listen to the Song of the Brain in Real Time,” in *Proc. IEEE NFSI-ICFBI’11*, 2011.

[32] G. Baier, T. Hermann, S. Sahle, and U. Stephani, “Sonified Epileptic Rhythms,” in *Proc. ICAD’06, London, UK*, 2006, pp. 148–151.

[33] G. Baier, T. Hermann, and U. Stephani, “Event-based sonification of EEG rhythms in real time,” *Clinical Neurophysiology*, vol. 118, no. 6, pp. 1377–1386, 2007.

[34] ——, “Multi-channel Sonification Of Human EEG,” in *Proc. ICAD’07, Montréal, Canada, June 26-29*, 2007.

[35] T. Hermann, T. Bovermann, E. Riedenklau, and R. Helge, “Tangible Computing For Interactive Sonification Of Multivariate Data,” in *Proc. ISon’2007*, York, UK, 2007.

[36] D. Wu, C.-Y. Li, and D.-Z. Yao, “Scale-free music of the brain,” *PloS one*, vol. 4, no. 6, p. e5915, Jan. 2009.

[37] D. Wu, C. Li, Y. Yin, C. Zhou, and D. Yao, “Music Composition from the Brain Signal: Representing the Mental State by Music,” *Computational Intelligence and Neuroscience*, p. doi: 10.1155/2010/267671, 2010.

[38] J. Lu, D. Wu, H. Yang, C. Luo, C.-Y. Li, and D.-Z. Yao, “Scale-Free Brain-Wave Music from Simultaneously EEG and fMRI Recordings,” *PloS one*, vol. 7, no. 11, p. e49773, Nov. 2012.

[39] T. Hermann, G. Baier, and M. Müller, “Polyrhythm in the Human Brain,” *Proc. ICAD’04*, vol. 1, 2004.

[40] A. De Campo, R. Hoeldrich, G. Eckel, and A. Wallisch, “New Sonification Tools For EEG Data Screening And Monitoring,” in *Proc. ICAD’07*, 2007.

[41] A. Brouse, J.-j. Filatriau, K. Gaitanis, R. Lehembre, B. Macq, E. Miranda, and A. Zénon, “An instrument of sound and visual creation driven by biological signals,” in *Proc. ENTERFACE’06*, Dubrovnik (Croatia)., 2006.

[42] T. Mullen, M. Luther, K. Way, and A. Jansch, “Minding the (Transatlantic) Gap: An Internet-Enabled Acoustic Brain-Computer Music Interface followed throughout the next decade by a number of artists,” in *Proc. NIME’11*, 2011.

[43] T. Hinterberger, N. Neumann, M. Pham, A. Kübler, A. Grether, N. Hofmayer, B. Wilhelm, H. Flor, and N. Birbaumer, "A multimodal brain-based feedback and communication system." *Experimental brain research*, vol. 154, no. 4, pp. 521–526, 2004.

[44] T. Hinterberger and G. Baier, "Parametric Orchestral Sonification of EEG in Real Time," *IEEE Multimedia*, vol. 12, no. 2, pp. 70–79, Apr. 2005.

[45] A. A. Trevisan and L. Jones, "Brain Music System: Brain Music Therapy Based on Real-Time Sonified Brain Signals," in *Proc. IET Seminar on Assisted Living*, London,, 2011.

[46] S. Mealla, M. Bosi, S. Jordà, and A. Väljamäe, "Sonification of Brain and Body Signals in Collaborative Tasks Using A Tabletop Musical Interface," in *Proc. ICAD11*, 2011.

[47] S. Le-Groux and P. Verschure, "Neuromuse: Training Your Brain Through Musical Interaction," *Proc. ICAD'09*, 2009.

[48] T. Hinterberger, "The Sensorium: A Multimodal Neurofeedback Environment," *Advances in Human-Computer Interaction*, vol. 2011, pp. 1–10, 2011.

[49] E. R. Miranda and V. Soucaret, "Mix-It-Yourself with a Brain-Computer Music Interface," in *Proc. 7th ICDVRAT with ArtAbilitation*, Maia, Portugal,, 2008, pp. 1–7.

[50] T. Hermann and G. Baier, "Sonic triptychon of the human brain," in *Proc. ICAD'10*, 2010, pp. 301–303.

[51] J. Eaton and E. R. Miranda, "New Approaches in Brain-Computer Music Interfacing," in *Proc. of Music, Music and Invention Workshop*, 2012.

[52] K. A. McCreadie, D. H. Coyle, and G. Prasad, "Learning to modulate sensorimotor rhythms with stereo auditory feedback for a brain-computer interface," in *Proc. IEEE EMBC'12*, San Diego, California USA, 2012.

[53] B. Swift, J. Sheridan, Y. Zhen, and H. J. Gardner, "Mind-modulated music in the mind attention interface," *Proc. CHISIG of Australia on Computer-human interaction: design: activities, artifacts and environments - OZCHI '07*, 2007.

[54] F. B. Vialatte, J. Dauwels, T. Musha, and A. Cichocki, "Audio representations of multi-channel EEG: a new tool for diagnosis of brain disorders." *American journal of neurodegenerative disease*, vol. 1, no. 3, pp. 292–304, Jan. 2012.

[55] D. Wu and D. Yao, "Chorus from the Two Brain hemispheres with Chinese Pentatonic Scale," in *Proc. IEEE IFMBE'13*, 2013.

[56] J. J. Filatriau, R. Lehembre, B. Macq, A. Brouse, and E. Miranda, "From EEG Signals To A World Of Sound And Visual Textures," in *Proc. ICASSP'07*, 2007.

[57] A. Kirke and E. R. Miranda, "Combining EEG Frontal Asymmetry Studies With Affective Algorithmic Composition And Expressive Performance Models," in *Proc. ICMC'11*, Huddersfield (UK), 2011.

[58] Z. Vamvakousis and R. Ramirez, "Temporal Control In the EyeHarp Gaze-Controlled Musical Interface," in *Proc. NIME'12*, Ann Arbor - Michigan, 2012.

[59] E. Jovanov, K. Wegner, V. Radivojević, D. Starcević, M. S. Quinn, and D. B. Karron, "Tactical audio and acoustic rendering in biomedical applications," *IEEE Transactions on Information Technology in Biomedicine*, vol. 3, no. 2, pp. 109–18, Jun. 1999.

[60] M. Elgendi, B. Rebsamen, A. Cichocki, and F. Vialatte, "Real-Time Wireless Sonification of Brain Signals," in *Proc. ICCN'11*, 2011.

[61] T. Hermann, G. Baier, U. Stephani, and R. Helge, "Vocal Sonification of Pathologic EEG Features," in *Proc. ICAD*, 2006, pp. 158–163.

[62] F. B. Vialatte and A. Cichocki, "Sparse Bump Sonification: A New Tool for Multichannel EEG Diagnosis of Mental Disorders; Application to the Detection of the Early Stage of Alzheimers Disease," in *Proc. ICONIP*, 2006.

[63] F. B. Vialatte and T. Musha, "Sparse Bump Sonification: a New Tool for Multichannel EEG Diagnosis of Brain Disorders," Riken Brain Science Institute, Tech. Rep., 2009.

[64] E. R. Miranda, S. Roberts, and M. Stokes, "On Generating EEG for Controlling Musical Systems," *Biomedizinische Technik*, vol. 49(1), pp. 75–76, 2004.

[65] E. R. Miranda, "Plymouth brain-computer music interfacing project: from EEG audio mixers to composition informed by cognitive neuroscience," *International Journal of Arts and Technology*, vol. 3(2/3):, pp. 154–176, 2010.

[66] C. R. Angel, "Creating Interactive Multimedia Works with Bio-data," in *Proc. NIME'11*, Oslo, Norway, 2011.

[67] R. W. Homan, J. Herman, and P. Purdy, "Cerebral location of international 1020 system electrode placement," *Electroencephalography and Clinical Neurophysiology*, vol. 66, no. 4, pp. 376 – 382, 1987.

[68] A. Tajadura-Jimenez, A. Valjamae, E. Asutay, and D. Vastfjall, "Embodied auditory perception: the emotional impact of approaching and receding sound sources," *Emotion*, vol. 10, no. 2, pp. 216–229, Apr 2010.

[69] P. W. Kaplan and S. R. Benbadis, "How to write an eeg report: Dos and donts," *Neurology*, vol. 80, no. 1 Supplement 1, pp. S43–S46, 2013.

[70] S. Barrass, M. Whitelaw, and F. Bailes, "Listening to the mind listening: An analysis of sonification reviews, designs and Correspondences," *Leonardo Music Journal*, vol. 16, no. 2006, pp. 13–19, 2006.

[71] "Google Glass," www.google.com/glass, 31/05/2013.

[72] A. Väljamäe, A. Tajadura-Jimenez, P. Larsson, D. Västfjäll, and M. Kleiner, "Binaural bone-conducted sound in virtual environments: Evaluation of a portable, multimodal motion simulator prototype," *Acoustical science and technology*, vol. 29, no. 2, pp. 149–155, 2008.

[73] M. M. Murray and M. Wallace, *The Neural Bases of Multisensory Processes*. Boca Raton (FL): CRC Press, 2012.

[74] E. Jovanov, D. Starcevic, V. Radivojevic, A. Samardzic, and V. Simeunovic, "Perceptualization of biomedical data. An experimental environment for visualization and sonification of brain electrical activity," *Engineering in Medicine and Biology Magazine, IEEE*, vol. 18, no. February, pp. 50–55, 1999.

[75] S. Mealla, A. Väljamäe, M. Bosi, and S. Jordà, "Listening to Your Brain : Implicit Interaction in Collaborative Music Performances," in *The International Conference on New Interfaces for Musical Expression (NIME)*, 2011.

[76] S. Mealla, S. Jordà, and A. Väljamäe, "Physiopucks: Augmenting music collaboration through physiology-driven tangible objects," in review.