VOCAL SONIFICATION OF PATHOLOGIC EEG FEATURES

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ABSTRACT

We introduce a novel approach in EEG data sonification for process monitoring and exploratory as well as comparative data analysis. The approach uses an excitory/articulatory speech model and a particularly selected parameter mapping to obtain auditory gestalts (or auditory objects) that correspond to features in the multivariate signals. The sonification is adaptable to patient-specific data patterns, so that only characteristic deviations from background behavior (pathologic features) are involved in the sonification rendering. Thus the approach combines data mining techniques and case-dependent sonification design to give an application-specific solution with high potential for clinical use. We explain the sonification technique in detail and present sound examples from clinical data sets.

Keywords: Sonification, EEG, Data Exploration, Process Monitoring

1. INTRODUCTION

The human brain is a highly complex information processing system, the comprehension of which is a major challenge of the new century. Although many new techniques have been added to observe the brain at work (like PET, fMRT, CT, and others), the standard electroencephalogram (EEG), the time-dependent, parallel measurement of electric potentials at various sites on the scalp, allows to record spatio-temporal electric activity at high temporal resolution (up to 2000 samples per second).

Unfortunately, EEG data provide only indirect spatial information about the sources of this activity, because neural activation at a given location within the cortex creates electric field potentials that are distributed over the scalp and are therefore picked up by more than one electrode. This leads to correlated time series, each representing a mixture of contributions from different neural sources. This makes the interpretation of individual pathologic features in EEG from standard montages difficult.

Human listening, however, is highly tuned to interpret mixtures of signals, to discern noise from patterns, and to make sense of multi-channel data series, demonstrated for instance by the 'cocktail party effect', or by the so-called synergistic listening that is applied when attending to complex soundscapes like a performing orchestra. Thus, the use of sonification to better understand complex EEG features is potentially beneficial but has been tried so far only in isolated and nonsystematic cases, see Hermann et al. [1], Baier and Hermann [2], Hinterberger and Baier [3], and references therein.

It is a basic feature of human listening to automatically categorize acoustic features by creating auditory gestalts (or auditory objects) from perceived sounds so that they become connected to a tangible meaning [4]. This can be observed, for instance, when listeners describe a newly heard sound as 'footsteps', 'a smashed glass', or as the sound of a particular car. Here we observe two tendencies: (a) categorization: semantically similar stimuli are grouped in one class. (b) fovea resolution: frequent listening to similar sounds causes the listener's auditory resolution to increase for the specific sort of stimuli, an effect which can be observed for instance in experienced car mechanics who are able to diagnose the causes of a malfunction even from subtle deviations of an engine's sound from normal. Although we assume the underlying auditory learning mechanisms to be highly general, we think that after the human brain has fully matured, its auditory resolution is biased to the differentiated processing of specific sorts of stimuli (e.g. language sounds and especially phonology). Thereby the human brain lacks full plasticity to adapt to other less common classes of sound signal groups. Evidence for that is given by language researchers. Speech is one class of sounds where listeners are probably more sensitive than with other classes of sounds; this might be the reason that nowadays listeners are still irritated by synthesized speech sounds whereas they have high acceptance for synthesized music instrument sounds.

The sonification technique developed in this paper addresses particularly the human's high auditory resolution in discerning vocal transients, by turning the ongoing EEG (in real-time or at any selected compression) into articulatory speech sounds. While there are infinite possibilities how this can be achieved, we motivate and select a highly specific yet generic way, that can be used independent of the number of utilized channels, the sampling resolution, the chosen montage, etc.).

We describe our specific application to epilepsy in Sec. 2, followed by an introduction of the sonification technique in Sec. 3. In Sec. 4 we present clinical data sets and discuss our sonifications. Since the sounds are in the domain of language we are even able to describe and reference to auditory objects by using textual descriptions. Finally we discuss our results on the background of a task-dependent design and conclude with mentioning some possible future work.

2. FEATURE EXTRACTION FOR GENERIC DATA DESCRIPTION

The sonification to be developed in the following section uses (a) personalized features, so that the listener can gain increased perceptual resolution for the subject under analysis, and at the same time can compare the sonifications between subjects; and (b) generic features, so that sonifications rendered from data recorded by a different EEG system (different number of channels, different temporal resolution, etc.) can be compared because they share the same logic. A current trend in clinical EEG is to increase the number of channels from the standard 10-20 (19 electrodes) system to the 10-10 system (32 electrodes) and to include more electrodes when necessary. Since, however, the interpretation of data sonifications requires some learning effort, we believe that the sonification techniques that allow 'stabilization' in the sense of convergence of sound patterns with increasing spatial resolution share a useful property.

The above requirements impose constraints for the features to be used for sonification, and this section introduces and explains the selected features.

2.1. State space analysis to characterize normal EEG behavior

We are interested in transiently abnormal EEG signals that show significant deviation from the patients 'typical' or normal EEG. Typicality can not be defined generally, since each brain 'ticks differently'. Thus we need to assess this measure at hand from selected EEG sections of a subject where electric activity can be assumed normal. The selection of this time series ideally covers different normal behaviors like relaxing, eyes open/eyes closed, sleeping, etc.. For the reason of simplicity, however, we here start by using a time window of normal EEG data that precedes a visually identified abnormality.

The state space is the Euclidean vector space formed by using all channel data $x_i(t)$ as a vector component of $\vec{x}(t)$. Then the EEG time series describes a trajectory in state space. Due to dependencies between the channels and individual properties, this state space is typically not completely 'filled' with data, but the data show variation only along a few subject-specific axes. Principal Component Analysis (PCA) [5] is suited to identify these linear dependencies and can be used to define a reference subspace in state space that covers 98% ($\alpha = 0.98$) of the variation. This is done by using only $q < d$ eigenvectors $\hat{u}_i$ of the data set covariance matrix C belonging to the largest eigenvalues λ_i so that

$$\sum_{i=1}^{q} \lambda_i > \alpha \cdot \mathrm{trace}(C) \ . \qquad (1)$$

In our examples, typically $q = 5 \ldots 7$ principal components suffice. Practically, we compute the normal subspace via singular vector decomposition (SVD) using octave[1]. Several features described next interpret the state space on the background of this PCA-defined normal activity.

2.2. Features to characterize transient pathologic activity

Figure 1 shows 6 representative EEG time series that include epileptic activity, and all features derived from the recording as described below.

Orthogonal distance from normal subspace. The first interesting feature is the instantaneous distance of the state space position to the linear subspace defined by normal activity:

$$d_S(\vec{x}(t)) = \sum_{i=q+1}^{d} \vec{x}(t)^T \hat{u}_i \qquad (2)$$

[1]http://www.octave.org

which already provides a good measure of abnormality of the brain state as compared to the background. d_S starts at label 1 on the y-axis of Figure 1. We see that activity in this feature correlates with epileptic activity in the time series.

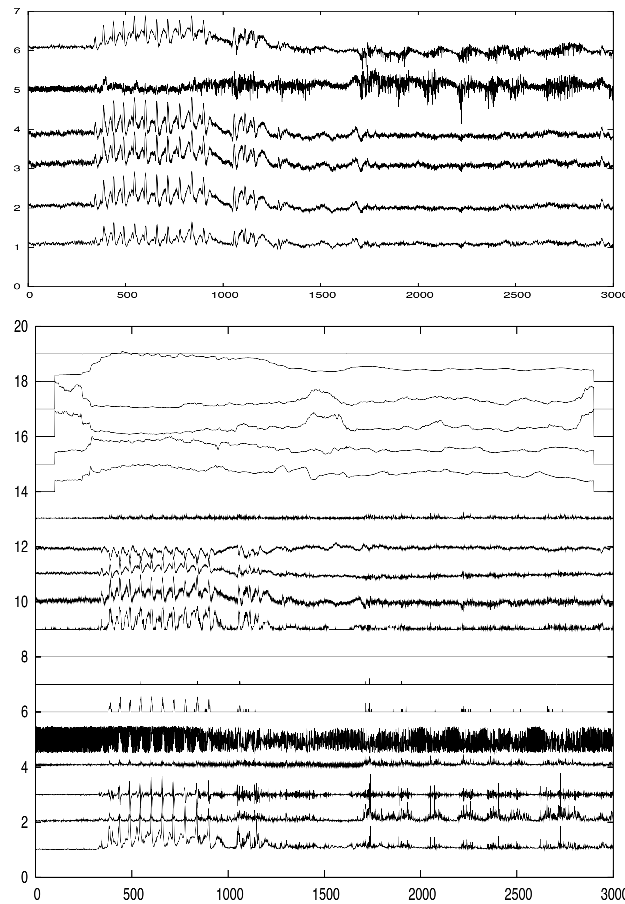

Figure 1: Top: 6 representative EEG time series including an epileptic episode. Below: The extracted feature variables described in the text. The feature's y-shift corresponds to the feature index given in Table 1.

The **velocity of orthogonal components in state space** is an interesting second feature since it detects rapid transients and thereby reflects sudden changes of the dynamics. The feature is computed by

$$v_S = \frac{1}{\Delta t} \left\| \sum_{k=q+1}^{d} \hat{u}_k (\vec{x}_k(t) - \vec{x}_k(t-1)) \right\|$$

The **derivative of distance from normal subspace** is the distance change $v_d = \partial d_S / \partial t$ with which the trajectory deviated from normal behavior.

The **data vector velocity** is the overall velocity of the movement of the state in state space. It is computed by

$$v_x = \frac{1}{\Delta t} \| \vec{x}(t) - \vec{x}(t-1)) \| \qquad (3)$$

The **curvature in state space** a_s is a feature that quantifies the change of direction a trajectory is taking at each point in time.

Practically this is done by computing the scalar product of successive normalized velocity vector estimates. Values around 1 correspond to straight motion, smaller values indicate stronger curvatures, up to -1, when the direction is reversed.
The **abnormality flags** are counters A_γ that describe at each point in time how many of the normal subspace components $\hat{u}_q\vec{x}$ exceed a threshold $\gamma\sigma_q$, where σ_q measures the standard deviation along axis $\hat{u}_q$. We compute this feature for different thresholds ($\gamma = 3, 5, 7$) corresponding to different degrees of probability that a given deviation qualifies as abnormal. Along the same line of reasoning we define the **number of amplitude outliers** A_{total}, which now operates on all electrode channels. These last four features are normalized so that their maximum is 1.

2.3. Spatial distribution features

Since we are interested in features that describe the electric potential distribution on the scalp in general terms, we here regard the data set as a limited sample of a continuous scalar potential field from which we can (theoretically) compute interpolated activity at each position, usually referred to as brain mapping. Feature variables are defined by scalar products of the interpolated function with characteristic spatial distributions, like for instance a hemispheric gradient. The central benefit of defining features according to this rationale is that it delivers defined features for any number and selection of electrodes.

Currently we use only two spatial features, namely the **hemispheric disbalance** and the **anterior-posterior disbalance**, defined as x and y-components of the dipole vector

$$D(t) = \sum_i \vec{r}_i x_i(t) \tag{4}$$

where $\vec{r}_i$ is the location of electrode i in space. Note that the weighted sum can be interpreted as a scalar product of a spatial basis function $b(\vec{v})$ with the spatial brain mapping,

$$\langle b, \vec{x}\rangle = \int_v b(\vec{v})\vec{x}(v)d^2v, \tag{5}$$

integrated over the scalp surface. Fig. 2 shows our basis functions plus one example for more complex basis functions which might be interesting for future sonifications, particularly if the spatial resolution increases. We suggest Gabor wavelets and multipole expansion series as particularly good starting points for such basis functions. Along the same line of argumentation are closely related features like the total potential X_{tot} (corresponding to a constant basis function) and derivatives of the scalar product. However, at present we only use the change of the dipole moment ΔD as a potentially interesting variable for sonification.

2.4. Correlation Matrix Features

Recent research results [6, 7] give evidence that the transition to absence seizures is accompanied by a characteristic change in the spectrum of the eigenvalues of the correlation matrix $C_w(t)$ of the windowed sphered data series, computed by

$$C_w(t) = \sum_{i=t}^{t+w} \vec{y}(i)\vec{y}(i)^T,$$

where $\vec{y}$ are transformed $\vec{x}$, shifted to zero mean and scaled to unit variance in the window. As the correlation changes are principally reflected at the edges of the spectrum, we use the two largest and the two smallest eigenvalues λ_1, λ_2, λ_{d-1}, λ_d as features, all of which we normalize to $[0, 1]$. The standard deviation in the chosen running window completes our list of features.

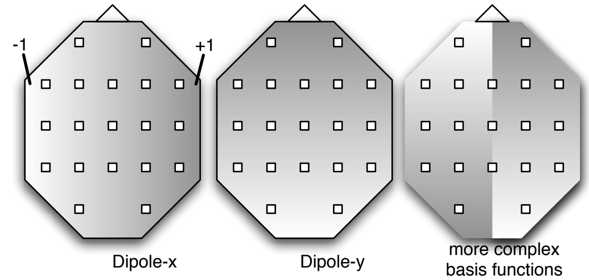

Figure 2: Basis functions for spatially distributed features, (a) hemispheric disbalance, (b) anterior-posterior disbalance, (c) an example for a more complex basis function.

With the above introduced set of feature variables we obtain a generic and task-oriented representation that abstracts from the detailed data sources (see Table 1). These variables are used within the sonification as described in the following section.

nr.	var	description
1	$d_s(x(t)$	Distance from normal subspace
2	v_s	Velocity of orthogonal components
3	v_d	Derivative of distance
4	v_x	Velocity of data vector
5	a_s	Curvature of data trajectory
6	A_3	Abnormality flag threshold=3
7	A_5	threshold=5
8	A_7	threshold=7
9	A_{total}	Outliers in data space (2σ-out ch.)
10	X_{total}	Overall potential of data (0th moment)
11	D_x	Hemispheric disbalance (dipole)
12	D_y	Anterior-posterior
13	ΔD	Change of dipole
14	λ_1	largest eigenvalue of C
15	λ_2	second largest eigenvalue of C
16	λ_{d-1}	second smallest eigenvalue of C
17	λ_d	smallest eigenvalue of C
18	σ_{win}	Standard deviation of window

Table 1: Summary of feature variables

3. VOCAL SONIFICATION TECHNIQUE

Using sounds from the domain of articulatory speech siarticulatorygnals enables listeners to make use of their highly adapted and well-trained speech perception skills for sound interpretation. Due to the sound production process, articulatory sounds cover a wide range of possible timbres, from noise-like transients over quasi-periodic fricatives to pitched and colored vowel sounds. The richness of speech sounds is not only created by the number of different timbre forms, but also due to the temporal structure, which is a result of acute rhythmical transitions between different vocal tract activities. Our listening is well adapted to constitute an auditory gestalt from well-formed spectro-temporal forms and denotes that as 'word'. Our approach is to connect articulatory synthesis parameters with data-driven feature variables in such a way that human listeners can make good use of their listening skills.

In this section we first explain our current approach to sound synthesis, then we motivate a mapping, which needs to be a good compromise between highest directness and adequate temporal sound structure.

3.1. Articulatory speech synthesis / Formant-Synthesis

From the physical basis, speech sounds can be explained as an exciter-resonator system with the lung as pressure/energy reservoir, the larynx (vocal folds) acting as nonlinear oscillator or source, and the mouth and nose channel acting as filters which are modulated by muscle activations of the tongue and lips [8]. Synthesis approaches thus start with a separation of signal source and filters. While periodic impulse (glottal pulses) lead to voiced speech, noise as source leads to unvoiced speech.

On the filter side, implementations range from cascaded bandpass filters to a detailed modeling of the throat and mouth shape using digital waveguides. The filters reshape the frequency profile of the harmonically rich source signal by attenuating or amplifying certain frequency ranges which are called formants. The first two formants suffice to distinguish the basic vowels a,e,i,o,u as in 'bath,bed,bin,bottle,boot'. Higher formants may support vowel distinction, but they typically contain cues for speaker identification. In this paper we keep the synthesis fairly simple by using a source-filter chain, yet we believe that more complex articulatory speech engines may increase discrimination and perceptibility of auditory gestalts. Basically the sound is defined by

$$s(t) = L \cdot \sum_{i=1}^{4} H_{bp}((\lambda z(t) + (1-\lambda)\eta(t); f_i, df_i, g_i)$$

where η is bandpass noise, $z(t)$ the impulse sequence, and $H_{bp}(s, f, df, g)$ a bandpass filter with center frequency f, bandwidth df and gain g. Voiced/unvoiced signals are obtained by adjusting $\lambda \in [0, 1]$.

While being only a very coarse model, this sound model already offers a reasonably high number of control parameters which now have to be fed in a reasonable way from features.

3.2. Mapping Design

The introduced sonification belongs to the class of indirect continuous parameter mapping sonification. The mapping is indirect in the sense that not data, but data-driven features are used to control synthesis parameters; it is continuous, since here a continuous sound signal is computed so that only a single speaker is perceived.

In the infinite space of mapping possibilities we try to motivate a specific choice at hand by plausibility arguments based on the type of data, the typical variability of parameters or task-oriented arguments. We hope that better mappings emerge during our ongoing process of model refinement, yet we believe that in the interest of the intended users (clinicians), at some point the mapping needs to be fixed in order to promote the listeners auditory learning processes. A concise representation of the mapping is given in Table 2.

One of the key interests is to rapidly identify abnormal EEG patterns, and to discern their dynamical properties. This suggests

parameter	feature	source	dest. range	scal.
L	$d_s(\vec{x}(t))$	[0, 1]	[-15, -5])	
λ	$d_s(\vec{x}(t))$	[0, 0.3]	[0, 1])	
f	v_s	[0, 2]	[100, 150])	
f_1	$3X_{total}$	[-1, 1]	[150, 1000]	tanh
f_2	$3D_x$	[-1, 1]	[300, 2500]	tanh
f_3	$3D_y$	[-1, 1]	[2000, 3800]	tanh
f_4	$3\Delta D$	[-1, 1]	[2500, 5000]	tanh
g_1	A_{total}	[0, 1]	[-15, -0])	
g_2	A_3	[0, 1]	[-15, -0])	
g_3	A_5	[0, 1]	[-15, -0])	
g_4	A_7	[0, 1]	[-15, -0])	

Table 2: Mapping for the vowel EEG sonification

to associate the abnormality features with an acoustic parameter that is able to switch from an inaudible (or nearly inaudible) to a clearly audible signal. In our synthesis this is the overall level (corresponding to the lung pressure), and the voice/noise ratio. This mapping basically causes the sonification to appear from a noisy background when signals are being regarded interesting enough require special attention. As a result the listener is not (or less) distracted by timbral variations in those parts that are explained from standard data variability, and is thus free to focus on the timbre evolution caused by the abnormal transients.

Pitch is a highly salient attribute, as is perhaps best evident from a singing voice. However, since here the main focus is to create rhythmical and vocal sounds, a too pronounced variation of pitch interferes destructively with timbral changes and even obscures timbral changes. From the currently employed features, we think that a velocity intuitively matches to frequency: the faster a repetition, the higher the frequency. We here choose the velocity in abnormal subspace for pitch control.

Next we control the formants from the spatial distribution features. The mapping from hemispheric disbalance to the first formant center frequency and anterior-posterior disbalance to the second formant center frequency is rather arbitrary, yet it is relevant that a mapping is not changed between sonifications since these mappings are needed to guarantee comparability. Finally we use the abnormality flags to drive the gains of the formants. This will basically allow better differentiation if a signal is likely to be abnormal. For mapping details see Table 2.

Fig. 3 shows a typical trajectory in formant space as it results from our technique. We see that the most frequent activity pattern is around the relaxed 'æ' sound near the center. Epileptic activity takes a trajectory which is almost circularly shaped and covers a more articulated range of vowels in the lower half of the figure. However, two formants do not suffice to fully explain the perceived auditory gestalt, and we think that with listening experiences patterns can be discerned beyond the obvious vocal transients.

3.3. Implementation

The sonification is programmed in two languages: octave and SuperCollider3 [9]. Octave, a free matlab clone, is ideal for efficient matrix computations. We use octave to generate a data set of the above described feature vectors from the input EEG data set. The sonification matrix is stored in a comma separated values file for manual inspection, plotting, and sonification.

The player routine in SuperCollider3 is a task (`TDef`), that

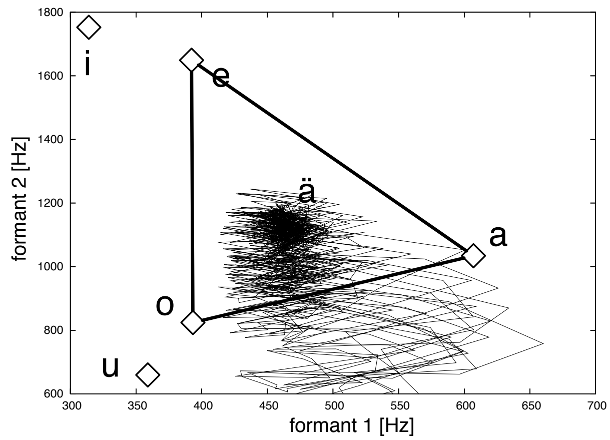

Figure 3: Formant space scatter plot, showing f_1 vs. f_2. Typical vowels are integrated as reference.

processes vectors in equidistant time steps, allowing control over the temporal compression and with the ability to navigate interactively in the data. Since the sonification is a continuous update of a single instance of a synthesizer, appropriate `/n_set` OSC messages are sent to the sound server.

For comfortable use we wrapped the core functions with some GUI controls as shown in Figure 4. The GUI currently allows to see a feature variable in synchronization with the sonification, to navigate the time axis and to adjust compression. We will provide the full sonification source on our website at [10].

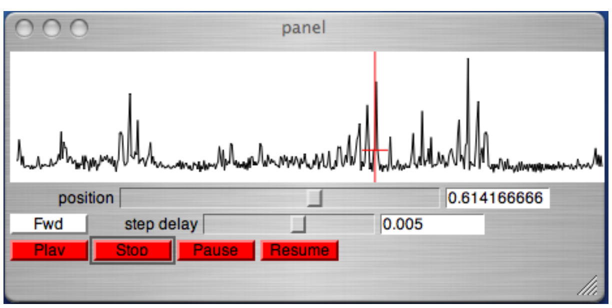

Figure 4: Graphical User Interface for Vocal EEG Sonification. The position and step delay (playback compression) can be adjusted interactively.

4. EXAMPLES

We now exemplify the proposed strategy with clinical EEG recordings from patients with epilepsy. In particular, a set of EEGs from children with generalized absence seizures was selected. The absence seizures are characterized by typical spike-wave patterns in the EEG that are picked up from all or most sites at the scalp. An important feature of this type of epilepsy is that the characteristic EEG abnormalities are often seen in a standard clinical recording even in the absence of a clinical seizure. They are thus likely to be found in short EEG segments during routine recordings and do not necessarily require long-term recordings which are only made in exceptional cases.

The recordings are 19 electrode standard EEGs in the 10-20 convention. Current source density montage was used as a spatial high-pass filter. The chosen segments contain groups of generalized spike-wave patterns with an average frequency of about 3 per second. This activity is spontaneous in the cases discussed here, i.e. no hyperventilation was ordered and no photic stimulation was applied.

Figure 5 shows the onset of epileptic activity from normal activity. The onset is nearly spontaneous, i.e. there is no visually evident "precursor" activity. However, upon closer inspection the onset of the first spike is earlier in some electrodes than in others. In the time series shown in the Figure, the epileptic activity sets in with a wave component and then continues with dominant spike-wave activity of large amplitude (as compared with background activity, c.f. the left half of the figure).

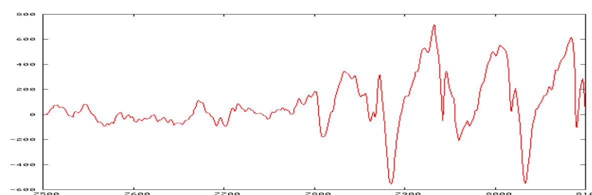

Figure 5: Potential of EEG channel Cz at the transition to absence seizure as a function of time.

Our first example is the sonification for the data shown in Fig. 1. The sonification covers only the first half which contains a sequence of spike wave formations. The real-time sonification of the 1500 steps lasts about 7.5s since the recording rate was 200 Hz. In S1, arising from a noisy background with low volume, a fast sequence of 'oiii-oiii-oiii-oiii' can be heard and a strict rhythmical pattern is very salient. Then after a short break the pattern changes to a second sequence of bursts that are better described as 'ya oiii ya oiii', with decreasing strength and dissolving regularity, until finally the pattern breaks down. Doubling the step delay (example S2), the vowel transitions are resolved better, and it can be heard that near the end 'i' as in 'bee' and 'e' as in 'bed' dominate over the darker vowels a or o. In S3 (4 times slower than real-time), even the temporal evolution of single spike wave patterns is resolved and the amplitude and its variation can be followed easily. Here, we can assign the 'ya' part of the repetitive complex to the slow-wave component and the 'oi' part to the sharp spike. In summary, we hear a rather continuous signal during epileptic activity and get a holistic impression about the dynamics via the sound.

This shall be compared with the second example where another child's data are sonified. In example S4 we hear the features of the EEG signal in real time and immediately perceive a much higher roughness in the activation. This segment consists of normal behavior that is interrupted in a burst like fashion by sequences of very fast spikes. Interestingly the bursts manifest themselves almost as a fricative 'r' or 'ch' sound. The vowel pattern is like an 'eyaaa eyar eyar eyar' and then, in the middle takes an unexpectedly slow 'ooo-ee-yaa–ee' sequence. When listening to the bursts at slower speed, as in S5 and S6, the source of this roughness becomes apparent: each burst consists of a sequence of very short and small spikes. We hear both the variation of velocity in state space as pitch and only minor vowel transitions. The last sound example (S7) resolves 4 bursts much higher and allows to discern that the vowel form itself modulates between the individual spikes in a burst. This, however is almost inaudible in real-time, and such fast tongue movements corresponding to the changes in timbre are impossible to execute with a human mouth.

Finally we present another sound example, S8, from a different EEG segment of the same patient. Again we hear the roughness, and feel immediately reminded of the patterns heard in the previous example (S4-S7). The sound is also similar, although the vocal transients now display a combination that might described rather by 'eyooo-eyooo-eyooo'.

A much more elaborated auditory investigation in collaboration with clinical experts is now needed to move from this first approach to the desired result: that EEG abnormalities like epileptic activity can be discerned, recognized and differentiated from muscle-induced artifacts under different background conditions by trained listening to the vocal EEG sonification.

5. DISCUSSION

The presented sonification exploits a highly promising field of acoustic signals, speech sounds, for the data-driven sonification of EEG recordings. In the design of the sonification, which is essentially an indirect continuous parameter mapping sonification, particular attention has been payed to generality in the sense that the sonification can be computed for all sorts of EEG data, independent of the number of available channels, the recording frequency, or the exact location of electrodes on the scalp. To achieve this, features have been computed which describe general properties of the underlying dynamics in state space. Particularly novel features in the context of sonification are the use of brain mapping scalar products with basis functions and the use of the windowed eigenvalues of the correlation matrix as quantifiers of time-dependent cross-correlations.

The sonification offers some means of interaction, concerning navigation and compression, and fuses sonification with a synchronized visual display which greatly supports orientation in the overall data set. Since the sonifications operate in a time resolution around real-time (although some features are better audible at slightly slower sonification), the technique may even be useful for online sonification.

Since data variations affect instantaneously the sound, the whole dynamics of sound variation is a direct consequence of variations in the data, and thus we attain a high temporal resolution. However, temporal sequences as they occur in verbal utterances (e.g. when saying words like "sonification", with voices/unvoiced parts interleaved, with plosives and fricatives, are rare in this mapping. We are not sure whether more severe manipulations of the temporal structure would be beneficial since this would go hand in hand with a degradation of directness. However, we would enjoy to enrich the current sonification in the direction of a higher variability of consonant particles. We think that this would be an important progress since it will enable human researchers to adapt to the sounds and to increase their understanding by tuning their listening to the rhythms and transients they might find characteristic in the sonifications.

6. CONCLUSION

In conclusion, our technique provides the basis for a more systematic use of sonification for browsing and scanning of EEG data, even for online applications. The fact that the sonifications occupy the sound space of vocal sounds with which human listeners are particularly familiar offers both the chance of a better sensitivity to changes in the dynamics, and the potential that researchers can more easily communicate structures and patterns in EEG data by mimicking the patterns with their own voice.

An essential condition for sonification to be successful is that the technique can be used without manual modifications in a large set of contexts, since only then, clinicians or other listeners can really tune to the sound space and apply auditory learning. Our approach favors such generality since it defines carefully a set of features which can be computed independent of the montage, number of channels, etc.

We are sure that improvements are possible and feasible, firstly, concerning the definition and selection of features; secondly concerning the mapping between these features and the sound synthesis techniques; and finally, in the implementation of more flexible and convincing articulatory speech models. These are the main three lines of research activities that we are facing for our ongoing research in Vocal EEG Sonification.

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