SONIFICATION TECHINIQUES APPLIED TO EEG SIGNALS OF NONMOTOR GENERALIZED ONSET EPILEPTIC SEIZURES

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Abstract: **The increased use of Electroencephalography (EEG) for the diagnosis of epileptic disorders in neuropediatrics has led to the development of technologies for the automatic reduction of redundant information. In modern EEG, pre-processing methods of the signal for artefacts removal and artificial intelligence algorithms for the recognition of critical events have been implemented.**
This work analyzes the application of sonification techniques to EEG signals for an almost real time assessment of epileptic seizures onset. Sonification concerns the transformation of numerical data into acoustic signals. EEG sonification could speed up its interpretation and reduce the amount of visual information to be analyzed. The dataset consists of 24 EEG recordings coming from 22 children with absence seizures, clinically evaluated at the Meyer Children's Hospital in Firenze, Italy. The obtained low false positive rate (<1%), shows the usefulness of EEG sonification techniques in supporting automatic and early seizure detection.

Keywords: **sonification, EEG, epilepsy, patient-specific, entropy.**

I. INTRODUCTION

Epilepsy is one of the main brain disorders, affecting about 1% of the world population [1]. It occurs mainly in childhood and increases, in terms of cumulative prevalence, in the elderly population [2]. Epilepsy, an enduring predisposition to manifest epileptic seizures, is also defined as "*a transient occurrence of signs and/or symptoms due to abnormal excessive and synchronous neuronal activity in the brain.*" [3], [4].

Given their high variability both in terms of aetiology, clinical signs, and electrophysiological characteristics, epileptic seizures are divided into several categories [5].

Electroencephalography (EEG) is one of the main technology supporting the diagnosis of epilepsy. The work presented here focuses on absence seizures, a type of generalized non-motor epileptic seizures [6]. The EEG signal of a patient with a typical absence shows generalized spike-wave discharges at 3Hz.
One of the main technological problems in the analysis of EEG signals in epilepsy is the presence of artefacts that, summed up to the data to be analyzed, can make the analysis in real time complex and burdensome.

In recent years there has been a growing interest in techniques allowing a near real-time clinical assessment of seizures (i.e. low latency times) [7, 8, 9], especially sonification. According to [10], sonification is defined as: "*the transformation of data relations into perceived relations in an acoustic signal for the purposes of facilitating communication or interpretation*".

Sonification can be used for performing a fast detection of clinical events or monitoring clinical information. Recently, Schwarz et al. [11] presented a psychoacoustic sonification technique for real time monitoring of neonatal oxygen saturation levels.

G.I. Mihalas et al. [12] gave several examples of physiological signal sonification, such as ECG, Heart Rate etc., and discussed their biomedical applications.

F.B. Vialatte et al. [13] used sonification techniques to discriminate EEGs of patients with mild cognitive impairment from those of healthy control subject.

Our recent paper [9] focused on techniques applied to the EEG signal for early seizure detection, along with artificial intelligence methods for the automatic recognition of absence seizures.

In the present work, the sonification techniques presented in [9] are analysed, with the purpose of reducing the false positive rates in the sonified EEG signals.

Patient-specific techniques are proposed to remove background noise from the sonified EEG signal. Moreover, methods are suggested for enhancing amplitude and patterns related to epileptic seizures or possible artefacts. Finally, similarly to [11], a statistical evaluation of the sonified EEG signal is presented, taking into account relevant differences between false

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positives not discarded by the automatic recognition process and the true epileptic seizures.

II. METHODS

To compare the performance of the proposed methods, the same EEG recordings used as test set in [9] and the same automatic recognition algorithms are considered here. The test set consists of 24 recordings of 22 children (7 males, 15 females, and age range 4 – 18 years) with absence seizures evaluated at the Paediatric Neurology Unit, Children's Hospital A. Meyer, Firenze, Italy. The duration of the signals is 47 ± 10 min with sampling frequency fs=256Hz. Written informed consent was obtained from all patients or their guardians.

The proposed methods are implemented under MATLAB software (version 2017b [14]) installed on a Hp Pavillion 15 notebook (OS Windows 10, 64 bit) Intel Core i7-5500U processor, CPU 2.40 GHz, RAM 16 Gb.

In [9] the automatic recognition gave 1% average percentage of false positives (FPR metric, ONLINE method) in the sonified signal. Here possible techniques that could further reduce false positives in the sonified signal are investigated.

The sonification procedure proposed in [9] is based on the following relationship:

$$[ABS - ABS - ABS] \rightarrow [beep_1 beep_2 \rightarrow sound_{abs}] \quad (1)$$

Eq. (1) is described as follows. If the automatic recognition step detects three (or more) consecutive absences (ABS), the first 2 consecutive seconds will produce 2 beeps (*beep*1 and *beep*2) as pre-alarms. This sound represents a first discrimination between a possible absence and a false positive.

As described in detail in [9], the following seconds classified as ABS produce the $sound_{abs}$. This is the sonified signal of the cumulated sum of the 6^{th} levels of decomposition of the EEG signals obtained applying the Stationary Wavelet Transform.

False positives are grouped into: background without intercritical activity, intercritical activity or, more generally, elements of electrophysiological interest of duration <2s, and artefacts.

Thus, methods that would allow the reduction or the recognition of these elements in the sonified signal are investigated.

As concerns the intercritical activity, in the dataset such segments have a time duration <3s. Being very similar to epileptic activity they are not removed.

To remove the background noise, a patient-specific adaptive method is implemented. The method is based on the assumption that, in this case, the signal shows lower energy contribution as compared to an epileptic absence seizure, mainly as its characteristic frequencies are concerned.

The proposed procedure is as follows. First, N windows (N = 100) with a duration of 2s each are selected from the signal. For each window the local maxima (V_{local}) of the rectified signal used for sonification are identified with a minimum distance between peaks given by 0.25*fs and their average value is calculated. Once all the windows and their average values are obtained (V_{mean_local}), a baseline is created for each patient given by the global mean value (V_{mean_global}).

From the window N+1 on, the windows such that $V_{mean\_local} \leq V_{mean\_global} + K{*}std(V_{local\,[1:N]})$ are excluded.

The evaluation of the artefacts is made directly on the sonified signal. Considering that the energy trend of the artefacts should be discontinuous with respect to an absence seizure (always around 3Hz), an amplification term α is introduced in the sonification equation [9]:

$$sound_{abs} = \alpha \sum_{i=1:N} E_{sound\_i} \sin(2\pi f_{osc} t) \quad (2)$$

where α is the square of the value of the peaks normalized with respect to their average and standard deviation and repeated for the minimum duration assigned to each peak. Quadratic amplification was chosen as a compromise between a linear amplification (difference between amplitude values difficult to detect) and an exponential one (excessive reduction of the sonified signal even with minimal differences in amplitude).

Therefore a sonified signal is obtained with periods of silence or discontinuous sound corresponding to artefacts, whereas for typical absences the amplitude of the signal is approximately constant.

Finally, likewise in [13], statistical tests are carried out to establish whether sonified signals of absence seizures are statistically different from false positives. In this work, the discriminant is the value of the Sample Entropy (SE) [15] in each time window of the sonified signal of length equal to 1s. The Mann Whitney test with significance level 0.05 is applied. For the Sample Entropy test, the embedding dimension *m* is set equal to 2 and the tolerance value *r* is set equal to 1.

III. RESULTS

The performance is evaluated with the same metrics as in [9]: Balanced Accuracy (BACC); F1score; Matthews Correlation Coefficients (MCC); False Positive Rate (FPR). The comparison between the methods is presented in Table 1.

TABLE 1 - Comparison of the proposed methods with the ONLINE method in [9]

Method	BACC	$F1_{score}$	MCC	FPR
Frassineti et al. [9]	89.0% ± 6.0%	69.0% ± 15.0%	0.70 ± 14.0	1.1% ± 1.0%
K=1	88.0% ± 6.0%	73.0% ± 14.0%	0.73 ± 13.0	0.8% ± 0.9%
K=2	86.0% ± 7.0%	72.0% ± 14.0%	0.72 ± 13.0	0.6% ± 0.7%
K=3	85.0% ± 8.0%	71.0% ± 13.0%	0.72 ± 13.0	0.5 % ± 0.7%

An example of qualitative comparison is shown in Figure 1 where the sonified signal of an epileptic seizure and its EEG are presented. The upper plot shows the EEG, the middle plot shows the result of sonification without the post-processing procedure, the lower plot shows the result obtained after the application of the proposed additional post-processing and amplification. Only one channel is shown.

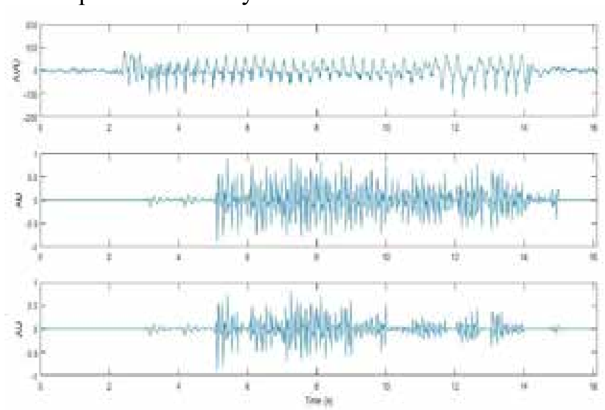

Figure 1 - Example of absence seizure sonification. Above: EEG signal (1 derivation); middle: sonification without post-processing; below: sonification with post-processing

Figure 2 shows an example of artefact and the corresponding sonified signal, before (middle plot) and after (lower plot) the application of the techniques described above.

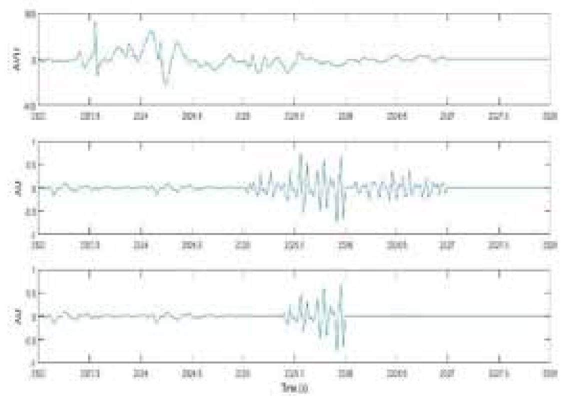

Figure 2 - Example of artefact sonification. Above: EEG signal (1 derivation); middle: sonification without post-processing; below: sonification with post-processing

Finally, the results of the statistical tests described in the previous section are presented in Table 2.

TABLE 2 - Statistical test results. Sample Entropy SE(m=2, r=1) case K=2.

Method	SE(2,1) – True Positive	SE(2,1) – False positive	p-value Mann Whitney
Frassineti et al. [9]	0.53 ± 0.14	0.51± 0.15	0.04
With α	0.35 ± 0.17	0.26 ± 0.16	3e^(-10)
With α and post-processing	0.34 ± 0.18	0.14 ± 0.19	1e^(-25)

IV. Discussion

Table 1 shows an increase of the performance especially for the FPR parameter that is reduced by almost 50% as compared to the case without post-processing. Also the $F1_{score}$ and MCC parameters increase with respect to the original ONLINE case. The decrease of the BACC parameter is an indication that some seizure windows (True Positive TP) were eliminated by the proposed method. Therefore, the choice of the parameter K must be made with caution to avoid losing useful information: indeed high values, such as K>3, could eliminate more seizures than artefacts. This point is under study.

Regarding the amplification parameter α of the sonified signals, with and without post-processing, the results of Table 2 (case K = 2) show significant differences between TP and FP (False Positive) rates.

Therefore, both the proposed techniques could alter the signal complexity, the TP Sample Entropy values decreasing more than the original ones, but less than the FP SE values. Possible reasons for this behaviour will be investigated in future developments of the methods.

Figures 1 and 2 and the statistical results of Table 2 show the possibility of detecting different events in the sonified signal, at least in terms of sound intensity and its repeatability. However, given the large variety of possible artefacts in the EEG signal, the proposed method cannot capture all possible variants. In particular, those that have a rhythmic energetic trend with frequencies close to 3Hz would be difficult to differentiate from the typical absence seizures.

Given the low number of atypical epileptic absence seizures in the dataset (2 recordings), no statistical tests were carried out to assess differences with typical absences in the sonified signal.

V. Conclusion

The application of post-processing and signal amplification techniques can lead to improvements both in terms of performance and qualitative recognition of events.

For a seizure detection system that applies sonification techniques the reduction of the FPR parameter seems relevant to reduce the amount of information to be analyzed.

The obtained statistical results allow performing validation experiments on the sonified signal [16]. The statistical evaluation of the sonified signal of atypical absences with respect to the typical ones will be one of the main future developments.

In conclusion, sonification techniques applied to EEG signals could introduce advantages for the real-time interpretation of information related to epileptic absence seizures. However, setting up sonification techniques for an easy removal of noise must be further exploited. If successful, they could help in reducing subjectivity and speed up the analysis.

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REFERENCES

[1] *Epilepsy Atlas 2005 World Health Organization*.
[2] E. Cesnik et al. "Incidence of epilepsy in Ferrara, Italy" *Springer, Neurol Sci (2013)* 34:2167-2172 doi 10.1007/s10072-013-1442-5.
[3] https://www.ilae.org/ last access: 10/09/2019
[4] R.S. Fisher et al. "Epileptic seizure and epilepsy: definitions proposed by the Internation League against Epilepsy (ILAE) and the International Bureau for Epilepsy (IBE)" *Epilepsia 2005*:46:470-472.
[5] R.S. Fischer et al. "Operational classification of seizure types by the International League Against Epilepsy: Position Paper of the ILAE Commission for Classification and Terminology." *Epilepsia. 2017* Apr;58(4):522-530. doi: 10.1111/epi.13670.
[6] C. E. Stafstrom et al. "Seizures and Epilepsy: An Overview for Neuroscientists" *Cold Spring Harb Perspect Med*. 2015 Jun 1;5(6) doi: 10.1101/cshperspect.a022426.
[7] M. E. Saab and J. Gotman, "A system to detect the onset of epileptic seizures in scalp EEG," *Clin. Neurophysiol*., vol. 116, no. 2. pp. 427–442, Feb. 2005.
[8] Vidyaratne, Lasitha S., Iftekharuddin, Khan M., 2017. "Real-time epileptic seizure detection using EEG". *IEEE Trans. Neural Syst. Rehabil. Eng*. 25 (11), 2146 –2156.
[9] Frassineti et al. "Automatic detection and sonification of nonmotor generalized onset epileptic seizures: Preliminary results" *Brain Research* 1721 (2019) 146341.
[10] Kramer, G., et al., 1999. "Sonification report: status of the field and research agenda." Tech. Rep., Int. Commun. Auditory Display
[11] S. Schwarz et al. "A psychoacoustic sound design for pulse oximetry" 25th International Conference on Auditory Display (ICAD 2019) 23-27 June 2019 https://doi.org/10.21785/icad2019.024
[12] G.I. Mihalas et al. "Can Sonification Become a Useful Tool for Medical Data Representation?" MEDINFO 2017: Precision Healthcare through Informatics A.V. Gundlapalli et al. (Eds.) 2017 International Medical Informatics Association (IMIA) and IOS Press. *doi:10.3233/978-1-61499-830-3-526*
[13] F.B. Vialatte et al. "Audio representations of multi-channel EEG: a new tool for diagnosis of brain disorders" *Am J Neurodegener Dis* 2012; 1(3):292-304.
[14] MATLAB and Statistics and Machine Learning Toolbox Release 2017b. The MathWorks, Inc., Natick, Massachusetts, United States.
[15] Richaman JS, Moorman JR. "Physiological timeseries analysis using approximate entropy and sample entropy." *Am J Physiol Heart Circ Physiol* 2000; 278: 2039-2049.
[16] Bonebright, T.L., 2011. "Evaluation of Auditory Display". In: Hermann, Thomas, Hunt, Andy, Neuhoff, John G. (Eds.), *The Sonification Handbook*. Logos Verlag, Berlin, Germany, pp. 111 –141.