ANALYZING MULTICHANNEL SCALP ELECTROENCEPHALOGRAMS OF PATIENTS WITH EPILEPSY USING EXPONENTIAL DATA MODELLING

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Abstract: The present paper reports for the first time on the multichannel analysis of scalp electroencephalograms based on exponential data modelling. We applied for this the subspace based pole estimation method HTLS (Hankel Total Least Squares). It was the aim of this study to investigate whether the multichannel HTLS method, which is often used in NMR spectroscopy, could detect the increased level of neuronal synchronization in the seizure EEG of patients with generalized and secondarily generalized seizures. The multichannel HTLS method allowed modelling the common dynamics of the different EEG channels. Based on the energy distribution of the common signal poles several measures were derived which which allowed for characterization of multichannel awake, sleep and epileptic seizure EEG in all patients studied. The derived information can be useful for automatic scoring of EEG and for detection of (secondarily) generalized seizures and sleep.

Keywords: scalp electroencephalography, epilepsy, multichannel analysis, exponential modelling, subspace based, HTLS, generalized seizures, secondarily generalized seizures, seizure detection.

INTRODUCTION

An epileptic seizure is a clinical manifestation due to an excessive and synchronized discharge of a group of neurons in the brain. These abnormal temporary manifestations of dramatically increased neuronal synchrony can occur focally (partial seizures) or bilaterally (generalized seizures). The seizure activity of partial seizures begins at the seizure focus and is then followed by a spread to adjacent or remote cerebral regions, at times resulting in secondarily generalized seizures. If consciousness is not impaired during a partial seizure then the seizure is classified as a simple partial seizure. If consciousness is impaired, then the partial seizure is classified as a complex partial seizure [1, 2]. In this paper we focus on signals measuring the electrical brain activity, the electroencephalogram (EEG), recorded on the scalp of epileptic patients suffering from generalized seizures or secondarily generalized seizures. All cerebral activity detectable by electroencephalography is a reflection of synchronous neuronal activity, so synchronous neuronal activity per se is not abnormal [3]. Epileptic seizures, however, are abnormal, temporary manifestations of dramatically increased neuronal synchrony which can be represented by periodic signals of low complexity. The period between seizures (interictal period) is characterized by a less orderly state of relatively low neuronal synchrony. The interictal period is represented by signals of increased complexity with multiple frequencies [3]. During generalized and secondarily generalized seizures most of the scalp EEG channels contain the same periodic signals of low complexity resulting in a high degree of common information in the different EEG channels. The aim of this study was to detect this decreased complexity and increased degree of common information of the seizure EEG by a multichannel analysis based on the subspace based pole estimation method HTLS (Hankel Total Least Squares) [4]. In this paper we will briefly describe the multichannel HTLS method [5], which is often used in NMR spectroscopy [5]. This method will be used to model all EEG channels with the same signal poles and based on the energy distribution of these signal poles several measures will be defined.

MATERIALS

We studied the electroencephalograms of 5 patients with epilepsy. The EEG recordings were performed on a 21-channel OSG EEG recorder. The electrodes were placed according to the extended international 10-20 System [6]. The scalp potentials were sampled at 250 Hz. For the analysis of the signals a reference montage was used. The data were filtered between 1 and 30 Hz with a bandpass filter (finite impulse-response). Three patients had Generalized Seizures (GS) and two patients had Complex Partial Seizures (CPS) evolving to Secondarily Generalized Seizures (SGS). Clinical seizure onset and end were determined by an epileptologist electroencephalographer. Table 1 gives an overview of the age, gender, type of seizure and, number of seizures applied for each patient. In this study we used three EEG recordings to explore the behavior of the proposed measures derived in the methods section. The three EEGs studied are shown in figure 1. In (A) the onset of a generalized seizure is presented. The seizure starts around t = 4.5 s. Record-

Patient	Age	Gender	Type of seizure	Number of seizures
P1	38	F	GS	2
P2	24	M	GS	1
P3	14	M	GS	6
P4	36	F	SGS	1
P5	26	M	SGS	1

Table 1: Patients information.

ing (B) shows a normal awake EEG, recording (C) is an EEG recorded during sleep. All EEG recordings are from patient P3 (cf. Table 1). In the generalized seizure EEG (recording (A) from t = 4.5 s to t = 10 s) we observe that most of the scalp EEG channels are represented by the same periodic signals of low complexity.

METHODS

Segmentation

We analyzed the data using a moving window technique which represents a common way of handling large amounts of data. The time series were divided into segments of 250 sampling points each, corresponding with a window length of 1 sec. The windows did not overlap.

Subspace based pole estimation method (HTLS)

A way to analyze EEG signals is to quantify them directly in the time domain by means of model-based (or parametric) methods. We used a method called HTLS [1] [4], where the EEG signal is modelled as a sum of K exponentially damped sinusoids:

$$\begin{aligned} \overline{y}(n) &= \sum_{k=1}^{K} a_k e^{j\phi_k} e^{(-d_k + j2\pi f_k)n\Delta t}, \qquad (1) \\ &= \sum_{k=1}^{K} c_k z_k^n, \\ n &= 0, 1, \ldots, N-1; \end{aligned}$$

with complex amplitudes

$$c_k = a_k e^{j\phi_k}, \qquad (2)$$

and signal poles

$$z_k = e^{(-d_k + j2\pi f_k)\Delta t}. \qquad (3)$$

$\overline{y}(n)$ represents the *n*-th modeled data point and Δt the constant sample interval between consecutive data points. The parameters to be determined are the frequencies f_k, dampings d_k, amplitudes a_k and phases ϕ_k. The model is a good approximation of the signal if the model order *(K)*, which is twice the number of frequency components, is chosen correctly. HTLS allows quantifying the frequencies more accurately with fewer data points than non-parametric methods such as the FFT (Fast Fourier Transform) [7]. Therefore, the method is better suited for non-stationary signals (like EEG signals). An interesting generalization is the multichannel HTLS [5], which allows to model the common dynamics of the different EEG channels at the same time. In this case the data

[1] HTLS is subspace-based pole estimation method that exploits the shift invariance property. It is an alternative to the TLS-ESPRIT method [7]: HTLS uses the singular value decomposition of the data matrix, whereas TLS-ESPRIT uses eigenvalue decomposition of the sample covariance matrix.

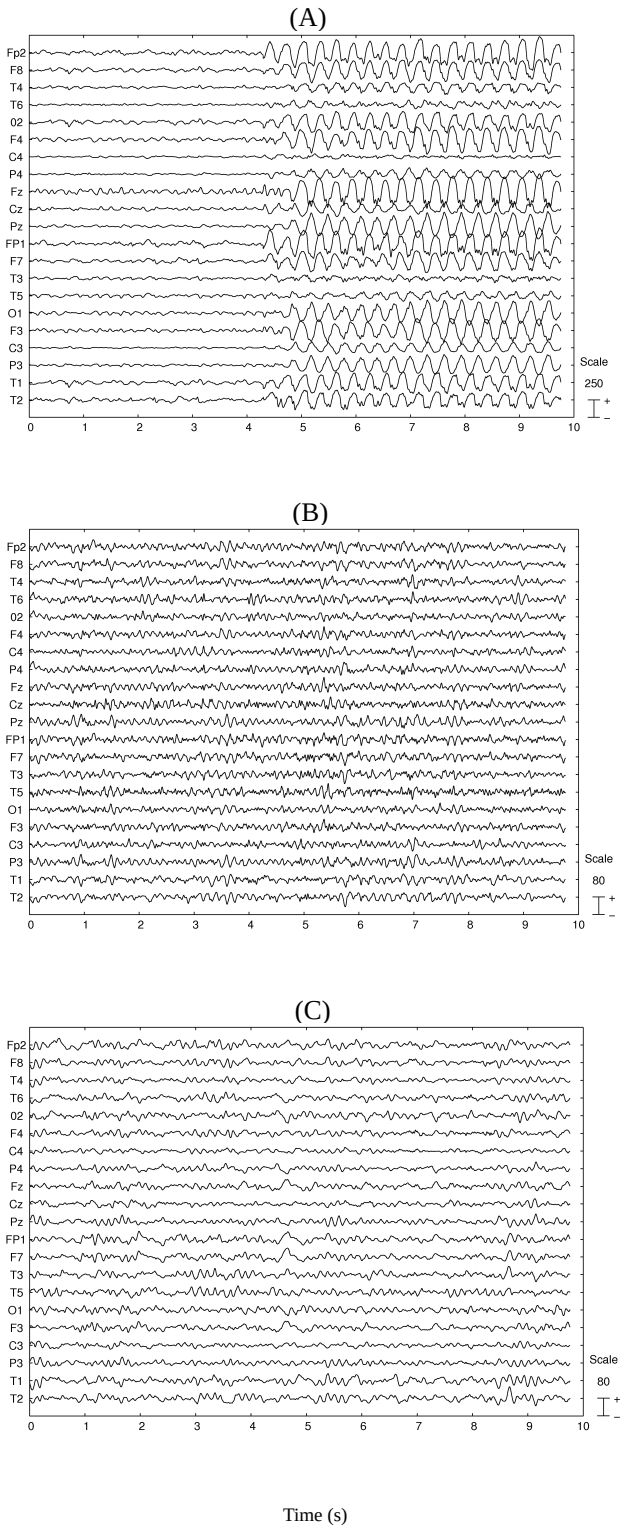


Fig. 1: (A) shows an EEG recording of the onset of a generalized seizure, starting at t = 4.5 s. Recording (B) shows a normal awake EEG and recording (C) represents an EEG recorded during sleep. The unit used on the Y-axis is μV.

from each EEG channel are arranged in separate Hankel matrices and these are stacked together in one block matrix. HTLS is applied to this matrix in order to extract common frequencies and dampings (signal poles). Once these common nonlinear parameters are identified, the corresponding amplitudes and phases are determined separately for each channel. More details about the algorithm and some applications can be found in [5, 7, 8].

Measures based on the energy distribution of the common signal poles

To get an idea of the common dynamics all EEG channels are modelled with multichannel HTLS and the energy distribution of the common signal poles is calculated. Equation 4 gives the multichannel model function; all EEG channels are modelled with common frequencies f_k and dampings d_k (signal poles z_k) but different amplitudes $a_k^{y_i}$ and phases $\phi_k^{y_i}$:

$$\begin{aligned} \overline{y}_i(n) &= \sum_{k=1}^{K} a_k^{y_i} e^{j\phi_k^{y_i}} e^{(-d_k+j2\pi f_k)n\Delta t}, \qquad (4) \\ &= \sum_{k=1}^{K} c_k^{y_i} z_k^n, \\ n &= 0, 1, \ldots, N-1; \\ i &= 1, 2, \ldots, I; \end{aligned}$$

with I equal to the number of EEG channels and N equal to the number of data points in a time window. Once the parameters are determined the energy of a signal pole z_k in channel i is computed as follows:

$$\begin{aligned} E(i,k) &= \sum_{n=0}^{N-1} |a_k^{y_i} e^{j\phi_k^{y_i}} e^{(-d_k+j2\pi f_k)n\Delta t}|^2, \quad (5) \\ n &= 0, 1, \ldots, N-1; \\ k &= 1, 2, \ldots, K; \\ i &= 1, 2, \ldots, I. \end{aligned}$$

To avoid that channels with a higher amplitude have a larger influence equation 5 is divided by the total energy of the channel. The relative energy contribution of signal pole z_k to channel i is given by :

$$\begin{aligned} E_r^{channel}(i,k) &= \frac{E(i,k)}{\sum_{n=0}^{N-1} \mid \overline{y}_i(n) \mid^2}, \qquad (6) \\ i &= 1, 2, \ldots, I; \\ k &= 1, 2, \ldots, K. \end{aligned}$$

The relative contribution of each signal pole to the total multichannel energy is determined as follows:

$$E_r^{multichannel}(k) = \frac{\sum_{i=1}^{I} E_r^{channel}(i,k)}{\sum_{k=1}^{K}\sum_{i=1}^{I} E_r^{channel}(i,k)}, \qquad (7)$$

$$k = 1, 2, \ldots, K.$$

Equation 7 represents the energy distribution of the common signal poles. In figure 2 the distribution of

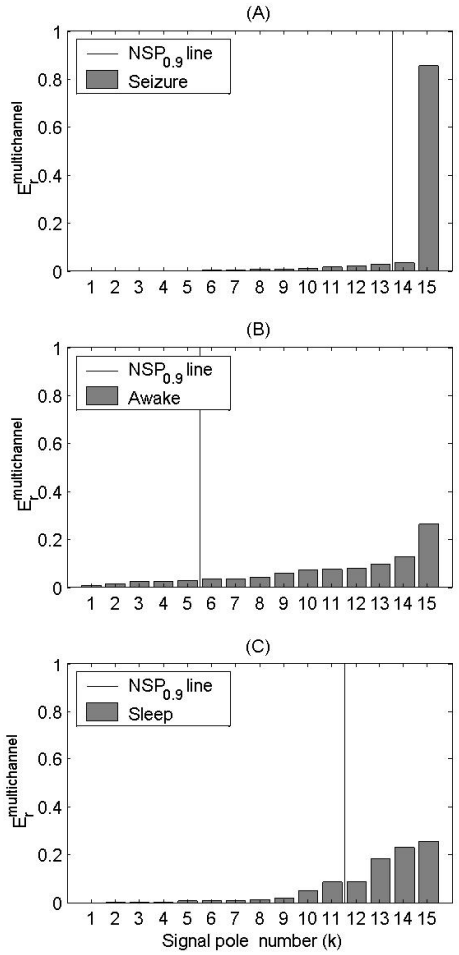


Fig. 2: Distribution of the $E_r^{multichannel}$(k) for a generalized seizure (A), awake (B) and sleep (C) segment of 1 second (patient P3) is shown. A vertical line is plotted at the 90% energy level. The signal poles on the right hand side of this line represent 90% of the total multichannel energy.

$E_r^{multichannel}(k)$ for the 15 first signal poles is shown for a seizure (A), awake (B) and sleep (C) EEG time window of 1 second. In this figure we see that for the seizure epoch more than 80% of the total energy is present in one signal pole indicating that one frequency component is dominant in many channels reflecting the increased neuronal synchrony during the generalized seizure. In the awake and sleep EEG epoch the energy is more evenly distributed among the various signal poles. For each distribution a vertical line is plotted at the 90% energy level. The signal poles on the right hand side of this line account for 90% of the total multichannel energy. A lower number of signal poles necessary to represent 90% of the energy indicates that the complexity of the multichannel EEG is lower. Again the complexity of the seizure EEG recording is lower because of the increased neuronal synchrony. The findings above have motivated us to define the following measures:

Most Active Signal Pole and E_{MASP}. The Most Active Signal Pole (MASP) is defined as the signal pole with the highest $E_r^{multichannel}(k)$:

$$E_{MASP} = max_k(E_r^{multichannel}(k)). \quad (8)$$

E_{MASP} represents the amount of energy that the most active signal pole contributes to the total energy. The higher the energy contribution of the most active signal pole to the total multichannel energy the more important this signal pole.

Frequency$_{MASP}$. The frequency of the most active signal pole is called frequency$_{MASP}$.

Multiplicity$_{MASP}$. The number of channels where the most active signal pole has the maximum energy contribution of all signal poles for that channel, divided by the total number of channels, is defined as multiplicity$_{MASP}$. If the MASP is the dominant signal pole in all EEG channels then the multiplicity$_{MASP}$ is equal to 1.

NSP$_{0.9}$. The Number of Signal Poles needed to represent 90% of the total multichannel energy is defined as NSP$_{0.9}$. A lower NSP$_{0.9}$ indicates that the complexity of the multichannel EEG epoch is lower.

RESULTS

First we will explore the behavior of the above defined measures on the three EEG recordings shown in figure 1. Subsequently the time evolution of the measures is evaluated on long term EEG recordings of all patients. These EEG recordings contain periods with normal awake, epileptic seizure and, sleep activity.

Case studies

Figure 3 shows the time course of the measures of recording (A) in figure 1. Because of the increased neuronal synchrony there is a strong increase in the energy and the multiplicity of the most active signal pole at seizure onset (t = 4.5 s). The energy of the MASP increases from $\sim$ 0.3 to $\sim$ 0.8 at seizure onset. The multiplicity$_{MAPS}$ increases from $\sim$ 0.5 to $\sim$ 1. These findings reflect the fact that the same frequency component becomes more important in all channels during the seizure because of the increased neuronal synchronization. The number of signal poles needed to account for 90% of the total energy drops at seizure onset from $\sim$ 7 signal poles to $\sim$2 signal poles indicating that the complexity of seizure EEG is lower. The frequency of the most active signal pole drops from 5 Hz before seizure onset to 3 Hz during the seizure (corresponding to the frequency of the epileptic activity). Figure 4 illustrates the time courses of the E$_{MASP}$, multiplicity$_{MASP}$, NSP$_{0.9}$ and frequency$_{MASP}$ for the three different recordings (i.e. seizure, awake, sleep)

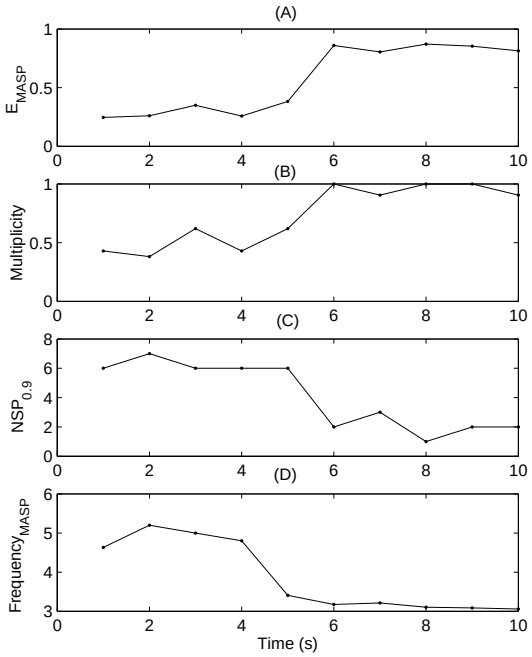


Fig. 3: Time course is shown of E$_{MASP}$ (A), multiplicity$_{MASP}$ (B), NSP$_{0.9}$ (C) and frequency$_{MASP}$ (D) of the EEG containing the generalized seizure onset (recording (A) shown in figure 1).

shown in figure 1. The energy and the multiplicity of the most active signal pole is higher for the seizure EEG than for the sleep and awake EEG recordings (figure 4 (A) and (B)). In the awake and sleep EEGs the energy is more evenly distributed than in the seizure EEG resulting in a lower E$_{MASP}$. The E$_{MASP}$ and multiplicity$_{MASP}$ of the awake EEG and sleep EEG are almost equal. The number of signal poles necessary to account for 90% of the total multichannel energy is lower for the seizure and sleep EEG recordings than for the awake EEG recording as shown in figure 4 (C) and figure 2. This analysis indicates that awake EEG epochs are of greater complexity than generalized seizures and sleep epochs.
As shown in figure 4 (D) the frequency of the most active signal pole in the awake EEG recording is around 8.5 Hz representing alpha activity. In the sleep recording the frequency of the MASP is around 7 Hz (theta activity). In the seizure onset recording the frequency of the most active signal pole drops from 5 Hz before seizure onset to 3 Hz during the seizure.

Long term EEG recordings

We applied the defined measures on long term EEG recordings of all patients containing periods with normal awake, epileptic seizure and sleep activity. We will discuss the results in two separate subsections depending on the type of seizure of the patient.

Generalized seizures. Figure 5 shows the time course of the E_{MASP}, multiplicity$_{MASP}$ and NSP$_{0.9}$ of patient

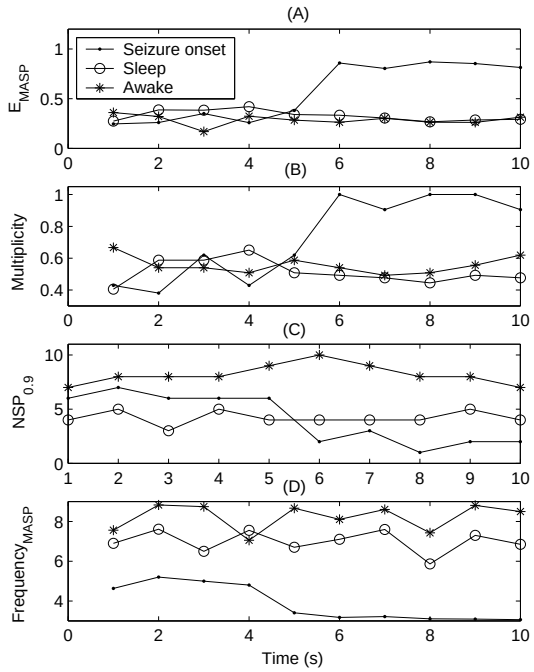


Fig. 4: E_{MASP} (A), $\mathrm{multiplicity}_{MASP}$ (B), $\mathrm{NSP}_{0.9}$ (C) and $\mathrm{frequency}_{MASP}$ (D) are shown for the three EEG recordings (i.e. seizure onset, awake and sleep) shown in figure 1.

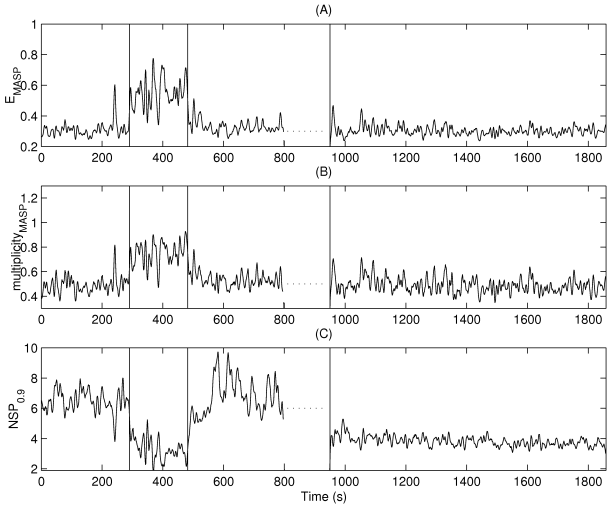


Fig. 5: Time course is shown of E_{MASP} (A), $\mathrm{multiplicity}_{MASP}$ (B) and $\mathrm{NSP}_{0.9}$ (C) for the analyzed EEG of patient P2. The generalized seizure is between the first two vertical lines. The horizontal dashed line represents 3 hour and 5 minutes of EEG. The sleep period starts from the third vertical line. A 3-point moving average filter has been applied for graphical display.

P2 (cf. Table 1). As shown the generalized seizure is characterized by a more active MASP (a higher E_{MASP}, $\mathrm{multiplicity}_{MASP}$) compared to the awake and sleep EEG. The sleep period is distinguished from the awake and seizure EEG because the $\mathrm{NSP}_{0.9}$ is lower than the awake $\mathrm{NSP}_{0.9}$ and the E_{MASP} is lower than the seizure E_{MASP}. Based on these findings we can conclude that the measures are able to distinguish three types of EEGs (i.e. awake, seizure and sleep). These conclusions can be generalized for all other patients with generalized seizures (i.e. patients P1, P2 and P3).

Secondarily generalized seizures. Figure 6 shows the time course of the E_{MASP}, $\mathrm{multiplicity}_{MASP}$ and $\mathrm{NSP}_{0.9}$ for patient P4 with complex partial secondarily generalized seizures (cf. Table 1). The end of the seizure is characterized by a more active MASP (a higher E_{MASP}, $\mathrm{multiplicity}_{MASP}$) compared to the awake and sleep EEG. This is the part where the seizure becomes secondarily generalized. The sleep period is distinguished from the awake and ictal EEG because the $\mathrm{NSP}_{0.9}$ is lower than the awake $\mathrm{NSP}_{0.9}$ and the E_{MASP} ($\mathrm{multiplicity}_{MASP}$) is lower than the ictal E_{MASP} ($\mathrm{multiplicity}_{MASP}$). The E_{MASP} and $\mathrm{multiplicity}_{MASP}$ do not increase during the first part of the seizure because the epileptic activity is only present in 3 out of 21 EEG channels. These measures do only increase when the same epileptic frequency is present in a large part of the 21 channels; this happens when the seizure becomes secondarily generalized. The same results were obtained for patient P5. These findings indicate that the measures can not be used for detection of partial seizures which do not evolve to secondarily generalized seizures.

DISCUSSION AND CONCLUSION

It was the aim of this study to investigate whether the multichannel HTLS method, which is often used in NMR spectroscopy, could detect the increased level of neuronal synchronization in the scalp EEG recordings of patients with (secondarily) generalized seizures. The multichannel HTLS method allowed modelling the common dynamics of the different EEG signals. Based on the energy distribution of the common signal poles several measures were derived which allowed to make the distinction between three types of EEG recordings containing awake, sleep and epileptic seizure activity in all patients studied. The information can be useful for automatic scoring of EEG or an automated detection system for generalized and secondarily generalized seizures and sleep EEG. Further research has to be conducted on the specificity and sensitivity of the derived measures. A comparison with existing multichannel methods [9] will be required. It has to be mentioned that the method does not detect complex partial seizures that do not evolve to secondarily generalized seizures. Furthermore we did not yet exploit the information contained in all complex damped exponential parameters such as the damping and phases. These parameters could be useful in the analysis of epileptic spikes-. The physiological meaning of the damping and phases will be subject of further research.

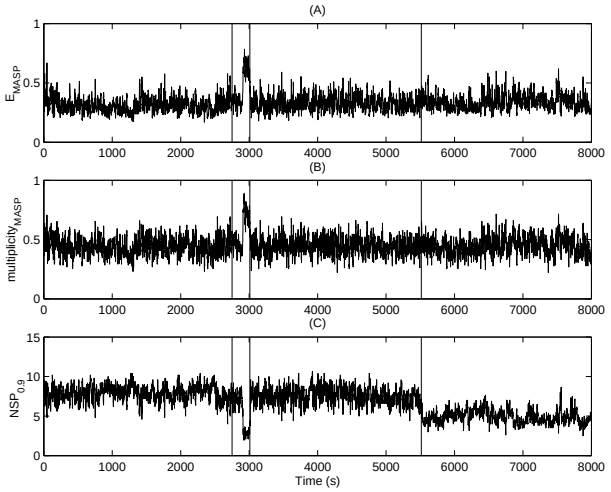


Fig. 6: Time course is shown of E_{MASP} (A), multiplicity$_{MASP}$ (B) and NSP$_{0.9}$ (C) for the analyzed EEG of patient P4. The seizure period is between the first two vertical lines. The sleep period starts from the third vertical line. A 3-point moving average filter has been applied for graphical display.

ACKNOWLEDGMENTS

W. De Clercq and P. Lemmerling are, respectively, research assistant and postdoctoral fellow of the Fund for Scientific Reserch-Flanders(Belgium) (FWO-Vlaanderen). Dr. Sabine Van Huffel is a full professor at the Katholieke Universiteit Leuven, Belgium. B. Vanrumste is a postdoctoral fellow at the Katholieke Universiteit Leuven in Belgium. Currently he is funded by the Programmatorische Federale Overheidsdienst Wetenschapsbeleid of the Belgian Government. Research is supported by Research Council KUL: GOA-Mefisto 666, IDO /99/003 and /02/009 (Predictive computer models for medical classification problems using patient data and expert knowledge), several PhD/postdoc and fellow grants; Flemish Government: FWO: PhD/postdoc grants, projects, G.0078.01 (structured matrices), G.0407.02 (support vector machines), G.0269.02 (magnetic resonance spectroscopic imaging), G.0270.02 (nonlinear Lp approximation), research communities (ICCoS, ANMMM); IWT: PhD Grants; Belgian Federal Science Policy Office IUAP P5/22 ('Dynamical Systems and Control: Computation, Identification and Modelling'); EU: PDT-COIL, BIOPATTERN, ETUMOUR.

REFERENCES

[1] Fisch B. Chapter 16: Classification of seizures. *In: Fisch,B. (Ed.), Fisch & Spehlmann's EEG primer, basic principals of digital and analog EEG. Elsevier*, pages 245–259, 1999.

[2] Jouny C.C., Franaszczuk P.J., and Bergey G.K. Characterization of epileptic seizure dynamics using Gabor atom density. *Clinical Neurophysiology*, 114:426–437, 2002.

[3] Bergey G.K. and Franaszczuk P.J. Epileptic seizures are characterized by changing signal complexity. *Clinical Neurophysiology*, 112:241–249, 2001.

[4] Van Huffel S., Chen H., and Decanniere C. et al. Algorithm for time-domain NMR data fitting based on total least squares. *J. Magn. Res. A*, 110:228–237, 1994.

[5] Vanhamme L. and Van Huffel S. Multichannel quantification of biomedical Magnetic Resonance Spectroscopic signals. *Advanced Signal Processing Algorithms, Architectures and implementations VIII, (Eds) Luk FT, Proceedings of SPIE*, 3461:237–248, 1998.

[6] Nuwer M.R., Comi G., and Emmerson R. et al. IFCN standards for digital recording of clinical EEG. *Electroencephalogr Clin Neurophysiol*, 106:259–261, 1998.

[7] Morren G., Van Huffel S., Helon I., Naulaers G., Daniels S., Devlieger H., and Casaer P. The effects of non-nutritive sucking on heart rate, respiration and oxygenation: a model-based signal processing approach. *Comparitive Biochemistry and Physiology*, Part A 132:97–106, 2002.

[8] Vanhamme L. Advanced time-domain methods for Nuclear Magnetic Resonance spectroscopy data analysis. *pH.D.-Thesis, Dept. of electrical engineering, Katholieke Universiteit Leuven, Leuven, Belgium*, 1999.

[9] Franaszczuk P.J. and Bergey G.K. An autoregressive method for the measurement of synchronization of interictal and ictal channels. *Biological Cybernetics*, 81:513–521, 1998.