Time varying neonatal seizure localization.

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Summary— **Background: A common cause for damage to the neonatal brain is a shortage in the oxygen supply to the brain or asphyxia. Neonatal seizures are the most frequent manifestation of neonatal neurologic disorders. Multichannel EEG recordings allow topographic localization of seizure foci. Objectives: We want to objectively determine the spatial distribution of the seizure on the scalp, the location in time and order the dominant sources in the brain based on their strength. Methods: In this paper we combine a method based on higher order CP-decomposition with subsequent singular value decomposition (SVD). Results: We illustrate the abilities of the method on simulated as well as on real neonatal seizure EEG. Conclusion: The proposed methods provide reliable time and spatial information about the seizure, gives a clear overview of what is going on in the EEG and allows easy interpretation.**

Keywords—CP-decomposition, Neonatal EEG, Seizure localization.

1. INTRODUCTION

A common cause for damage to the neonatal brain is a shortage in the oxygen supply to the brain or asphyxia. This damage has important consequences for the development of the child. Neonatal seizures are the most frequent major manifestation of neonatal neurologic disorders [1]. Most seizures are subclinical, being detected only by EEG monitoring [2, 3, 4]. Interpretation of the neonatal EEG requires specific expertise, which is normally not present in the neonatal intensive care unit (NICU). Therefore, there is a need for automated monitoring techniques eliminating constant on-site supervision.

We developed an automated neonatal seizure detection method with low false positive rate and high sensitivity [5]. After detection, it is important to localize the seizures and determine the brain region involved. Recently, we developed an automated seizure localization technique using Canonical Decomposition (also known as Parallel Factor Analysis (PARAFAC), often referred to as the CP-decomposition) that separates the seizure activity from the other concurrent EEG activity [6]. This technique allows us to obtain a reliable spatial distribution of the seizure on the scalp. A drawback of this method is the assumption of a fixed localization for the complete window of analysis as the whole window is analyzed at once. The method is not optimized to extract seizure activity in a situation where the seizure activity is shorter in duration than the complete window under analysis. Furthermore, we would like a method that is also able to give time information about exactly when the extracted activity is present in the window under analysis and is able to give an intuitive order of the importance of each extracted activity in the EEG.

In this paper, we propose a method to reliably extract seizure activity using the CP-decomposition. A subsequent post processing step based on Singular Value Decomposition (SVD) provides time information and gives an intuitive order of the importance of the extracted activity. The CP decomposition for EEG analysis was introduced fairly recently [7]. Subsequent work [6, 8, 9] has shown that the CP decomposition can provide a reliable estimate of the epileptic seizure onset zone. We start by introducing the CP decomposition. Next, we describe the SVD post processing step and illustrate the application of the method on simulated and real neonatal EEG.

2. MATERIALS AND METHODS

2.1 Dataset

The data was recorded at the Sophia Children's Hospital (part of the University Medical Center Rotterdam, the Netherlands). The data is from a patient with perinatal asphyxia. The full 10-20 set of electrodes (17 electrodes: Fp1,2, F3,4, C3,4, Cz, P3,4, F7,8, T3,4, T5,6, O1,2) was used. Sampling frequency was 256 Hz. Before analysis, the data was filtered between 0.3 and 30Hz.

2.2 Methods

The trilinear CP model for a three-way array $X^{(I\times J\times K)}$ is given by:

$$x_{ijk} = \sum_{r=1}^{R} a_{ir} b_{jr} c_{kr} + e_{ijk} \qquad (1)$$

where R is the number of components used in the CP model and e_{ijk} are the residuals containing the unexplained variation. A pictorial representation of the CP decomposition with R atoms is given in Fig. 1. The CP model is a trilinear model: fixing the parameters in two modes, x_{ijk} is expressed as a linear function of the remaining parameters. The CP decomposition is usually computed by means of an Alternating Least Squares (ALS) algorithm [9]. This means that the cost function

$$f(A,B,C) = \left\| X - \sum_{r=1}^{R} A_r \circ B_r \circ C_r \right\|^2 \qquad (2)$$

is iteratively minimized by means of alternating updates of one of its matrix arguments, keeping the other two matrices fixed. Because the CP decomposition is a multi-linear decomposition, each update just amounts to solving a classical linear least-squares problem.

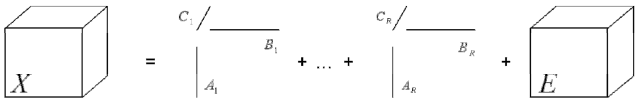


Figure 1: Pictorial representation of the CP decomposition with R atoms.

CP decomposition is applied on a third-order tensor, but an EEG is only a two dimensional signal with dimensions channel and time. The third dimension of the tensor is constructed using the continuous wavelet transform of the EEG recording [7]. The tensor then consists of dimensions channel, time and frequency.

The wavelet transform is chosen for its optimal time-frequency resolution. Wavelets resolve high frequency components within small time windows and low frequencies in larger time windows. The continuous wavelet C at scale a and time t of a signal $x(t)$ is defined by

$$C(a,time) = \int_{-\infty}^{\infty} x(t)\phi(a,time,t)dt \qquad (3)$$

with ϕ the chosen wavelet.

According to previous studies, we used a biorthogonal wavelet with decomposition order 3. We took those frequency components with a center frequency f_c ranging from 1Hz up to 30Hz with a step of 1Hz.

To cope with several types of activity that are active during only a limited amount of time in the window of analysis, we divide the EEG into several short, overlapping windows. We chose to take windows of 2 s with an overlap of 0.5 s between consecutive windows as this is a good compromise between time resolution and having enough data points for a reliable signal separation. A tensor is constructed of each window with a continuous wavelet as described above. Subsequently, the tensor is decomposed using a 2-atom CP-decomposition. By checking the Core Consistency Diagnostic, we found the optimal number of atoms to be two. This decomposition leads to two extracted time vectors (components B1 and B2, see Fig. 2), two localization vectors (A1 and A2) containing the spatial distribution of the extracted time series and two frequency distribution vectors (C1 and C2). For the purpose of localizing the seizures, we are particularly interested in the two localization vectors per window. Both localization vectors of each window are collected in the rows of one matrix which we refer to as the *A-matrix* (Fig. 2). SVD decomposes a matrix into orthogonal components and orders them in order to their contribution. SVD applied to the *A-matrix* allows us to extract the dominant sources. The right eigenvector (matrix V in Fig. 2) corresponding to the singular value with the highest relative power (s_1) is the spatial distribution of the dominant source in the complete EEG. The left eigenvectors (matrix U in Fig. 2) contain the time occurrence of the activity in the window under analysis. The relative power of the singular value can be calculated using:

$$S_i = \frac{s_i^2}{\sum_{j=1}^{N} s_j^2} \qquad (4)$$

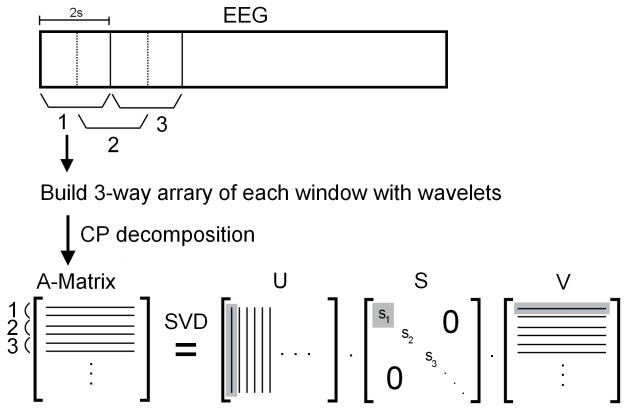


Figure 2: Schematic overview of the CP-SVD method. The *A-matrix* consists of 2 localization vectors for each EEG-window. An SVD analysis is performed on this *A-matrix*. The spatial distribution vector in matrix *V* corresponding to the largest singular value s_1 is the spatial distribution of the dominant source in the complete EEG.

3. RESULTS

3.1 Simulation

We define the performance of the method on the simulated EEG signal shown in Fig. 3. The simulated signal consists of 2 sine waves corrupted by noise. The first sine wave of 2Hz is set at the 2 frontal Fp channels; the second of 4Hz is

set at channels F8 and T3. Both are active during half of the entire window and are non-overlapping.

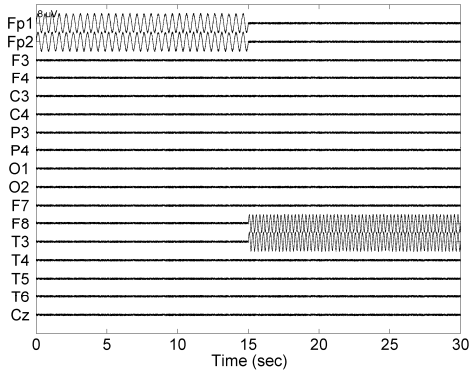


Figure 3: Simulated EEG signal with oscillations on the frontal channels and on channels F8, T3.

Fig. 4 shows a visualization of the *A-Matrix* that contains all the A-components of the subsequent CP-decompositions applied on overlapping 2 s windows. This figure shows that the first half of all the windows contain strong activity on the frontal Fp channels and the second half of the analysis contains strong activity on channels F8 and T3.

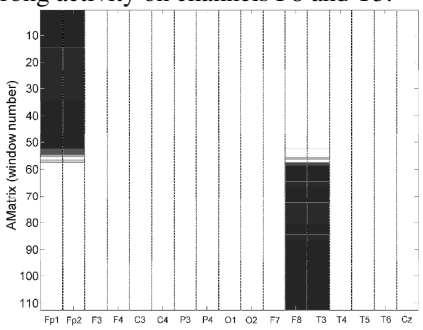


Figure 4: Visualization of the *A-Matrix* containing all spatial distribution vectors extracted by the subsequent CP calculations on the simulated signal.

The subsequent SVD analysis calculated on the *A-Matrix* shown in Fig. 5 reveals that there are 2 dominant components present in the simulated signal with a relative strength, calculated using the power of the singular values, of 50.5% and 49.5%. The topographic plots are the spatial distributions corresponding to the first two right eigenvectors in Fig. 2 (Matrix *V*). Correlation of these U-vectors with the original simulated mixing of the sources is equal to 1, meaning exact reconstruction and no influence of the noise. The curves below the topographic plots show the distribution of the activity over the extracted spatial distributions in the *A-matrix* (*U*-matrix of the SVD analysis) and give an indication of the time occurrence of the detected activity. The frontal activity is clearly active during the first half of the window and the other activity during the second half.

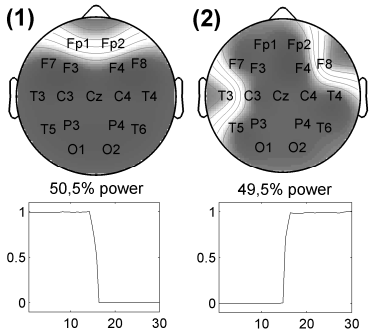


Figure 5: Results of the CP-SVD method applied on the simulated EEG shown in Fig. 3.

3.2 Illustration

We will illustrate the application of the algorithm on the neonatal EEG displayed in Fig. 6. There are three important types of activity present in this EEG. There is an oscillatory seizure present on the occipital channel O1. There are horizontal eye movements on the frontal channels Fp1 and Fp2, starting from second 22. And finally, there is a burst (between seconds 10 to 15), predominantly present right temporally.

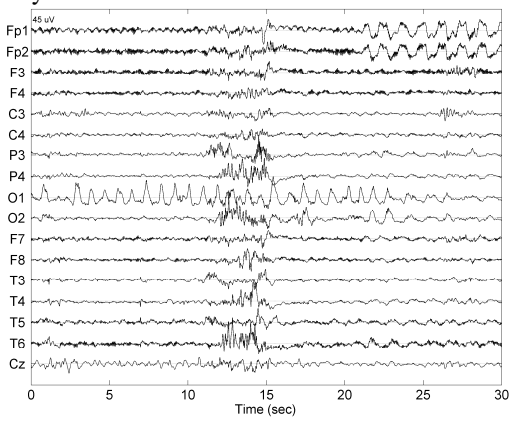


Figure 6: Example of an oscillatory seizure predominantly present on channel O1. On the frontal channels Fp1 and Fp2 another oscillation is present due to horizontal eye movements. Between 10 and 15s a burst of activity is present predominantly right temporally.

Fig. 7 shows the visualization of the *A-Matrix* that contains all the A-components of the subsequent CP-decompositions applied on the EEG of Fig. 6. The three dominant types of activity can clearly be identified on this plot. The first A-components contain activity on channel O1. Between A-components 40 to 60 the more dispersed burst activity can be seen and at the end, the eye movements on the frontal channels are dominant. The results shown in Fig. 8 of the subsequent SVD analysis on this *A-Matrix* reveal the dominant sources. Only the first 4 dominant sources are shown. The topographic plots of the first 4 right eigenvectors (matrix *V*) show occipital, frontal and right temporal activity.

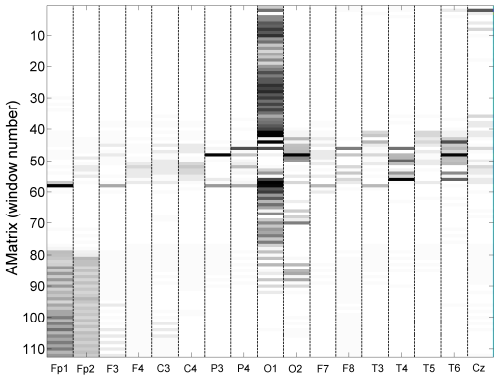


Figure 7: Visualization of the *A-Matrix* containing all spatial distribution vectors extracted by the subsequent CP calculations on the real EEG.

The seizure activity and eye movements are nicely separated from each other, the burst activity is split up between two sources. The seizure activity is the strongest source in the EEG with a relative power of the singular value of 54%, followed by the eye movements with a power of 30%. The plots of the left eigenvectors (*U*-matrix) reveal the time occurrence of each activity. The seizure activity at O1 is strongest in the beginning, fading at the end and with a dip in the middle due to the burst. The frontal activity is strongest at the end. The two burst sources are clearly strongest in the middle of the window under analysis.

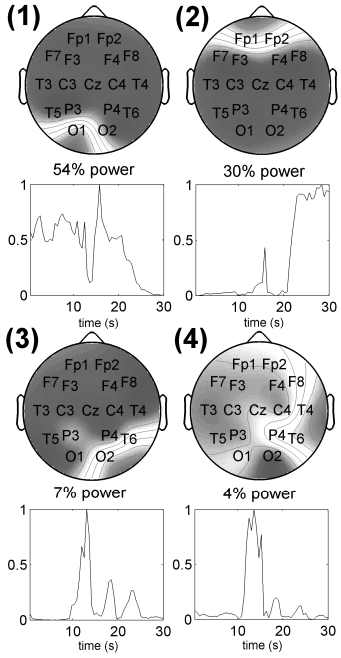


Figure 8: Results of the CP-SVD analysis of the EEG shown in Fig. 6. The four first eigenvectors of the SVD analysis are shown here. The topographic plots correspond to the first three right eigenvectors of matrix *V* in Fig. 2. The value under each topographic plot is the relative power of the singular value and the curves at the bottom, display the distribution over the extracted spatial distributions in the *A-matrix* (matrix *U* in Fig. 2).

4. CONCLUSION

In this paper, we introduce a new approach to extract the spatial distribution of the dominant sources in an EEG window, provide time information about when the sources are active and give a natural order of the strength of the sources in the EEG. The method splits the EEG up in 2 s windows and builds a third-order tensor in which the first two dimensions are space and time and the third dimension is constructed by decomposing the EEG into different frequency components. The subsequent CP-decomposition of each tensor provides us with reliable spatial distributions which can be grouped in a matrix called the *A-matrix*. Visualization of this matrix (Fig. 5 and 8) shows the value, as the time/localization information of the matrix is easily interpretable. SVD analysis of this *A-matrix* allows us to calculate the strength of each source using the power of the singular values. The left eigenvectors give us the time information when the source is active during the window and the right eigenvectors give us the topographic information of the extracted activity. Combination of this information gives us a clear overview of what is going on in the EEG and allows easy interpretation.

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