Contemporary Engineering Sciences, Vol. 4, 2011, no. 1, 25 - 35

Identification and Characterization of the Sources of the Noise Affecting the Visual Evoked Potentials

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Abstract

Single visual evoked potential (VEP) responses are completely buried in the background noise. For this reason, powerful extraction separating useful signal from the noise is needed to improve their clinical use which assume most of the time that the noise is Gaussian and additive. While the true VEP signal informs about the sensory functioning of the visual system, the study of the background noise may also be useful to identify the nature of the noise and its correlation with the true signal and other parameters that may be linked to the central nervous system diseases.

In this study, we attempted to identify the number of the sources generating the background noise using blind sources separation methods. In particular, best results were obtained with the second-order blind identification – robust orthogonalization (SOBI-RO) algorithm. Characterization of the sources were performed through computation of their power spectral densities and compared to those of synthetic colored noise. Preliminary results showed that the number of noise sources and their characteristics may inform on the central nervous system functioning.

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Keywords: Visual Evoked Potential (VEP), Colored noise, Power spectral density, SOBI-RO

1 Introduction

The visual evoked potentials (VEP) are responses elicited by the brain under a visual stimulation. These signals are completely buried in a background noise. The noise is originating from various sources which hide a major part of the VEP waveform and often make waveforms analysis quite difficult if not impossible. Essentially, we can distinguish between the electronic noise that is introduced by the data acquisition system, used in the clinical tests and the biological noise resulted from the spontaneous biochemical and electrical activity of the brain and the presence of several layers between neurons and the recording electrodes (bone of the skull, cerebrospinal liquid,...) [7], [8],[10].

In the clinical practice, the averaging technique is commonly used to extract the VEP meaningful signals. The concept is to average most of the single responses during the recording session until a clean plot of the VEP is obtained. This often requires the acquisition of several single brain responses [13], [17], [19].

Theoretically, this technique stipulates that the VEP signals are stationary, and supposes that the noise that affects them is additive and the true VEP is reproducible from one trial to another. In several studies, the additive noise is spectrally flat with either zero or weak time correlations. However, these hypotheses cannot be justified in the case of the VEP because this one presents a non stationary character whereas the noise is not very well known. Therefore, the averaging method results in a loss of information especially when the number of responses becomes large [10], [13], [17], [19]. To overcome these problems, several filtering techniques were proposed as alternatives to extract VEP, the most recent one was based on a nonlinear adaptive filter using a three layer percepton [9]. This filter, not only allows us to achieve a better approximation of the VEP, but also enables us to get the noise mixture which is the difference between the input and the output of the filter as shown in the following synoptic scheme bellow. Consequently, it becomes possible for us to study the noise signal in order to achieve a better understanding of its nature [9].

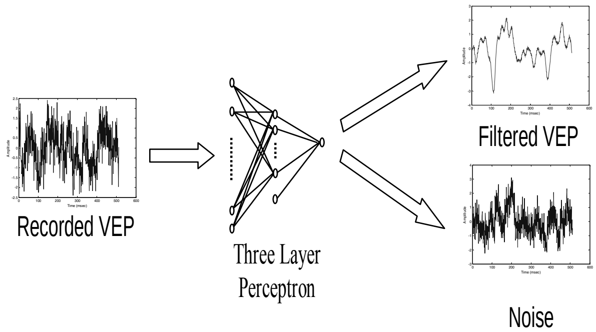


Fig.1: the noise mixture extraction scheme [9].

In this study, we attempt to isolate the noise sources in which the true VEP is embedded using Blind Sources Separation (BSS) methods. In fact, BSS were successfully used in many application areas, including medical diagnosis (ECG, EMG, EEG,…) [1], [2]. In our application, once the sources are separated, we identify their spectral characteristics that we compare them to those of synthetic colored noise. Tests of theses techniques are performed on the basis of 110 real VEP data, collected from a normal subject (50 single responses) and from a pathological case (60 single responses)

2 Methodology

Second-order blind source separation: SOBI-RO Algorithm

The Blind Source Separation (BSS) is used in several fields such as astronomy, seismology, biomedical engineering, etc. It deals with recovering a set of underlying sources from observations without knowing the mixture process and sources [1], [3].

In this work, we choose a BSS approach which exploits non stationarity properties and second order statistics (SOS). In fact, the non stationarity is proved that a simple decorrelation technique is able to perform the BSS task. However, we are mainly interested in the second-order non stationarity in the sense that source variances vary in time [1].

Let x(t) represents n-dimensional vector that corresponds to the n continuous time series from the noise data. Then $x_i(t)$ corresponds to the continuous sensor readings from the i^{th} electrode. Each $x_i(t)$ can be assumed to be an instantaneous linear mixture of n unknown components or sources $s_i(t)$, via the unknown n x n mixing matrix A, as expressed below

$$x(t) = A\,s(t) \qquad (1)$$

The BSS approach uses the measurement x(t) and nothing else to generate an n x n demixing matrix W that approximates A^{-1}, and the vector of the estimated component or putative source values defined by:

$$\hat{s}(t) = W \; x(t) \qquad (2)$$

The time courses of the components are given by ŝ(t) and the sensor projections of the components are given by the estimated mixing matrix $\hat{A} = W^{-1}$. Each column of Â indicates the effect of that component, in isolation, on all sensors [1].
In order to evaluate the effectiveness of the used algorithm, we calculate the performance index (PI) which is defined by the following equation:

$$PI = \frac{1}{n(n-1)} \sum_{i=1}^{n} \left\{ \left(\sum_{k=1}^{n} \frac{|g_{ik}|}{\max_j |g_{ij}|} - 1 \right) + \left(\sum_{k=1}^{n} \frac{|g_{ki}|}{\max_j |g_{ji}|} - 1 \right) \right\} \qquad (3)$$

where g_{ij} is the (i,j) element of the global system matrix G = WH and $\max_j(g_{ij})$ represents the maximum value among the elements in the i^{th} row vector of G. Also, the term $\max_j(g_{ji})$ corresponds to the maximum value among the elements in the i^{th} column vector of G [1].

When the perfect separation is achieved, the performance index is zero. In practice, a performance index around 10^{-2} indicates quite a good performance [1].

As we demonstrated in a previous work [7], the noise signal mixtures have colored Gaussian characteristics with identical power spectra shapes. In this case, the non stationarity information based methods, in contrast to other approaches, allow the separation of such sources.

Many methods of BSS were tested. The choice of the appropriate algorithm is based on the PI defined above. In this way, the Second-order Blind Identification – Robust Orthogonalization (SOBI-RO) algorithm is found (table 1) to be the most effective BSS technique which consists in decomposing n-channel mixture into n-components, each of which corresponds to a recovered putative source that contributes to the noise signal.

This method exploits the zero time-lag covariance matrices after the conventional whitening of the observations. The robust orthogonalization consists in finding a linear transformation such that the global mixing matrix will be orthogonal and unbiased by an additive white noise. Such robust orthogonalization is an important pre-processing step in a variety of BSS methods. It ensures that the global mixing matrix is orthogonal [1], [2], [4], [5], [6].

Power spectral density of colored noise

The sources being extracted, in both normal and pathological cases, were analyzed through the computation of their PSD functions which we compared to the one of a generated colored noise with nonzero correlation time [15], [16].

Indeed, a colored noise ξ(t) is a time-correlated Ornstein-Uhlenbeck process which exhibits an exponential correlation function such as:

$$\langle \xi(t)\, \xi(s) \rangle = \left(\frac{D}{\tau}\right) e^{-|t-s|/\tau} \qquad (3)$$

where we designate the noise intensity as D and the noise correlation time as τ.

It is shown that all kinds of colored noise are characterized by their power spectrum (Fourier transform of the correlation function) which is given by the equation (4):

$$S_{\xi}(\omega) = 2D/(\tau^2\omega^2 + 1) \qquad (4)$$

This function with a $1/f^{\beta}$ shape like has been observed in many biological systems [3]. In a previous study, we have shown that the noise that affects the VEP signals is not a white one. For this reason, in this study, we tested two kinds of colored noises with values of β=1 and β=2 which have been observed in many biological systems. These values of β correspond to pink and brown noise [11], [16], [13], [21]. Thus, the PSD of pink noise decreases 3dB per octave with increasing frequency (density proportional to 1/f) over a finite frequency range (figure 2). Each octave contains the same amount of power. It can be synthesized using the Voss-McCartney algorithm which consists in adding multiple white noise sources at lower and lower octaves [14], [20].

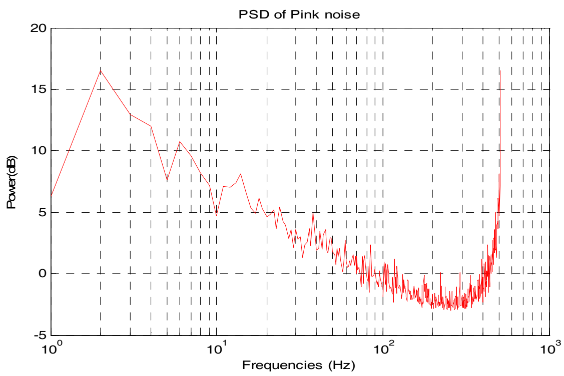


Fig. 2: PSD of a pink noise

For the brown noise, commonly designed by “random walk” or “drunkard’s walk” noise, the PSD decreases 6dB per octave with increasing frequency (density proportional to $1/f^2$) over a frequency range as the figure 3 below illustrates [14], [18], [21].

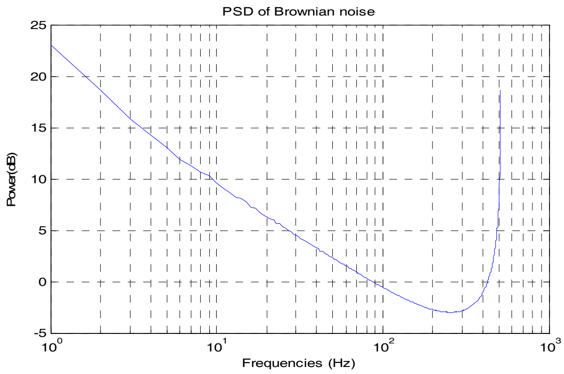


Fig. 3: PSD of a brown noise

3 Experiments and results

In this section, some experimental results with real-world signals are presented. The tests have been about a set of 50 raw VEP signals that correspond to a normal subject and 60 raw VEP corresponding to a pathological one. We have used in our study the ICALABSP TOOLBOX [1], [12]. This tool contains a collection of algorithms for blind source separation (BSS) employing the second order statistics (SOS) and higher order statistics (HOS).

As a first step, we have applied three different BSS algorithms and we have calculated their corresponding PI. As the table bellows shows, the most appropriate method for processing our data is the SOBI-RO algorithm performing the lowest PI.

Table 1: Performance Index (PI) of the three tested BSS algorithms

Algorithm	Pathological case	Normal case
AMUSE	0,02576	0,04501
SOBI	0,02535	0,05615
SOBI-RO	0,02501	0,03997

In the second step, we have applied the SOBI-RO algorithm to our set of data. We processed five continuous time series by five from the noise mixture signals.

3.1 Application to the normal case

In the normal case, the noise mixtures are formed by four independent components as shown in the figure 4.

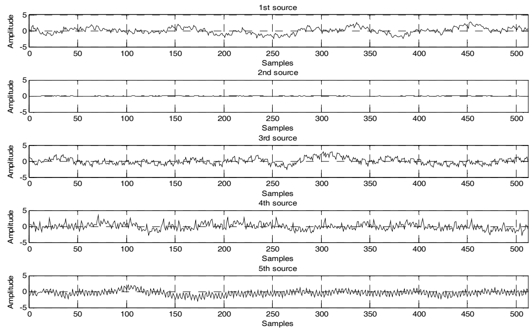
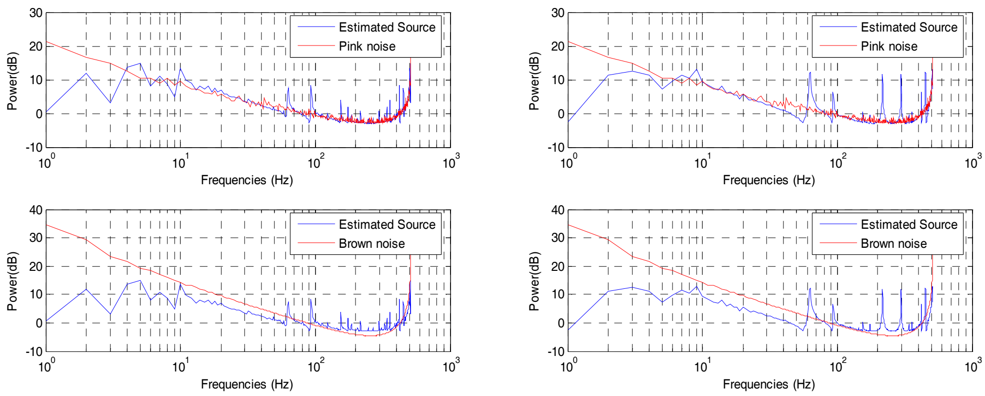


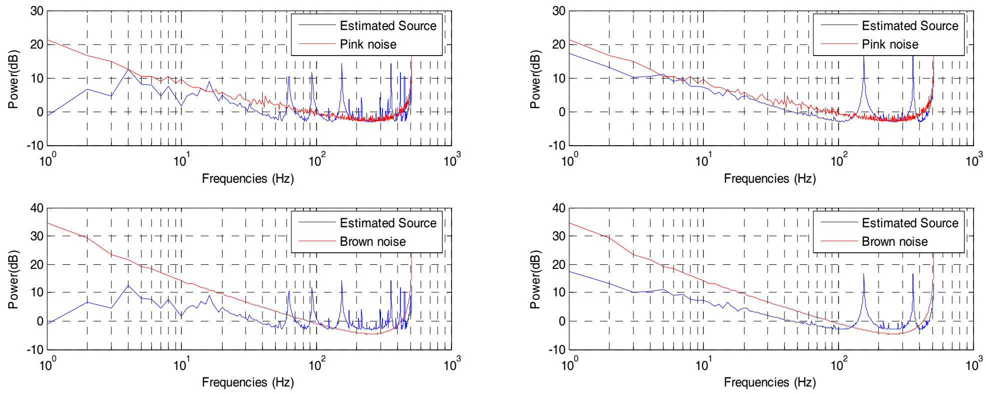
Fig.4: The estimated noise sources in the normal case.

We compared the computed PSD functions to the one of a theoretically generated pink and brown noise. The figure 5 bellow illustrates the results found in this study.

Indeed, by comparing the PSD shape of plots, we notice that in the normal case, all the estimated sources act as a pink noise rather than as a brown noise, especially in the range of frequencies [0Hz, 100Hz]. In the higher frequencies range, the sources present some peaks of energy that appears randomly. Furthermore, the spectrum of the fourth independent component is strongly close to a pink noise. It also presents two additional characteristic peaks that correspond to the frequencies [140Hz; 150Hz] and [375Hz; 385Hz] respectively as the plot of the figure 5.d shows.



(a) (b)



(c) (d)

Fig.5. PSD of noise source Vs PSD of a pink noise (top) and brown noise (bottom) in normal cases.

3.2 Application to the pathological case

In the pathological case, the result shows that the noise mixtures are formed by two main independent components (figure 6). The calculation of the correlation between these two components is practically close to zero which means that the identified sources are well independent (figure 7).

We have also calculated the PSD functions of each isolated noise source. We have found that these functions have the same shape of plot. We have noticed that the spectrum decrease with a logarithmic form with frequencies in the range [4Hz; 400Hz]. In this range of frequencies, the PSD function of the estimated sources look like the one of a pink noise rather than the one of a brown noise. The figure 8 illustrates these results.

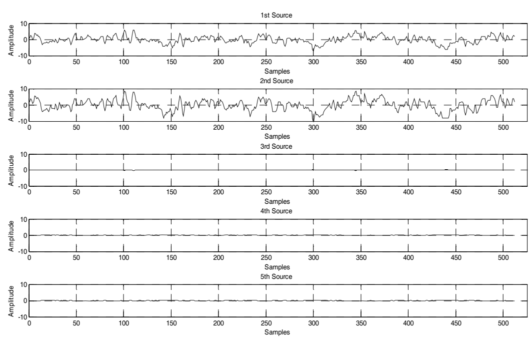


Fig.6: Estimated noise sources in the pathological case.

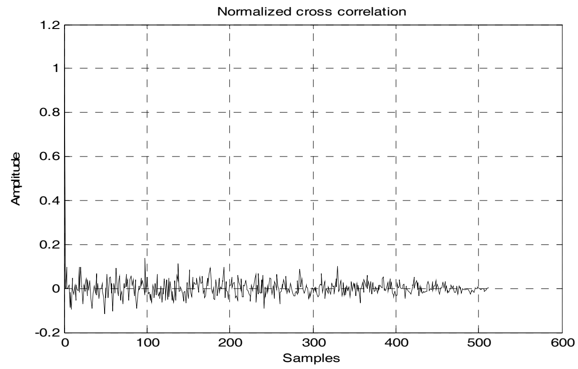


Fig.7: Cross-correlation function of the two estimated noise sources.

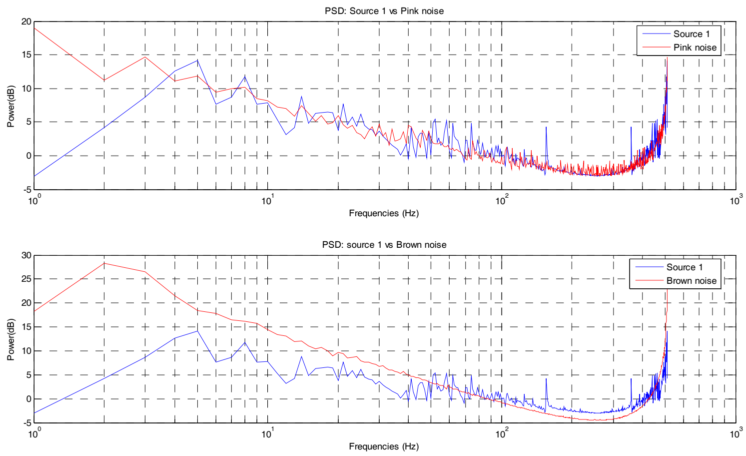


Fig.8. PSD of noise source Vs PSD of a pink noise (top) and brown noise (bottom) in pathological case.

Our investigation aimed to find if there is any relationship between the separated noise sources in both normal and pathological cases. For this reason, we have calculated the correlation between normal extracted sources and pathological ones. The figure 9 shows that a strong correlation exists between the first normal noise component and the pathological one. Consequently, we can deduce that this source is common between the normal case and the pathological one.

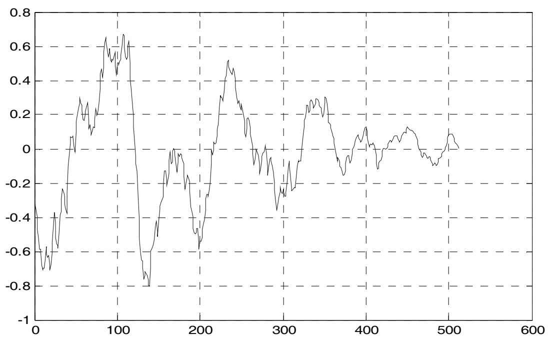


Fig.9. Normalized cross-correlation function between the first normal estimated noise's source and the pathological estimated one.

4 Conclusion

In this article we have presented the results of the blind separation of the noise sources affecting the visual evoked potentials. The noise signals are gotten through a non linear filtering method applied to original VEP. We applied the SOBI-RO method to 110 extracted mixtures of noise which correspond to both a normal subject and a pathological one.
Blind source separation showed that in the normal case, the noise mixture is formed by four isolated sources. By comparison with both pink and brown noise, we have noticed that all estimated sources act as a pink noise in the range of frequencies [0Hz, 100Hz]. In the higher frequencies range, the sources present some peaks of energy that appears randomly. The frequency spectrum of the fourth normal independent component presents two additional characteristic peaks situated in the frequency ranges [140Hz; 150Hz] and [375Hz; 385Hz] respectively.
In the pathological case, two independent components only were found. They have practically the same shape of plot of the power spectrum which looks like the one of pink noise within the range of frequencies [4Hz, 400Hz]. Furthermore
We have found that, for all the single responses tested, the normal and the pathological case share the same characteristics of the first noise component.
These preliminary results suggest that the background noise in which the VEP signal is embedded is not a white Gaussian noise as assumed in most VEP studies. Further investigation is needed to check the link between the number and characteristics of the noise components in VEP recordings and the brain functioning.

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Received: July, 2010