Identification of Visual Evoked Potentials in EEG detection by Emprical Mode Decomposition

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***Abstract*— Visual Evoked Potentials (VEPs) are referred to electrical potentials due to brief visual stimuli which can be recorded from scalp overlying visual cortex. A way to measure VEPs is through encephalogram (EEG). VEPs are very important because they can quantify functional integrity of the optic pathway. Their study allows to detect abnormalities that affect the visual pathways or visual cortex in the brain, and so methods that permit to identify VEPs components in EEG signals must be defined. However, the background activity measured from EEG hides VEPs components because they have a low voltage. So it is necessary to define a robust method to extract features, which best describe these potentials of interest. In this work Empirical Mode Decomposition (EMD) method is used to separate the EEG components and to detect VEPs. EMD decomposes a signal into components named Intrinsic Mode Functions (IFM). The results, obtained from the study of EEG records of a normal person, suggest that IMFs may be used to determine VEPs in EEG and to obtain important information related to brain activity by a time and frequency analysis of IMF components. It is well comparable with the known Wavelet Transform method, but it is characterized from a greater simplicity of implementation because the basis used in the analysis is generated by the same analyzed signal.**

Keywords—Evoked Potentials, EEG, Empirical Mode Decomposition

I. Introduction

EEG is a record of the spontaneous electrical activity of groups of neurons located in the head through electrodes placed on the scalp of the patient [1]. It is one of the main methods for the extraction of information from the brain for research and clinical purposes, and so to detect neurophysiological and physiological disorders [2,3]. In fact, the electrical activity of the brain causes the time differences of potential variations on the surface of the head, and the electroencephalogram is a measure of these potentials between the electrodes on the head. However it is also useful to record another type of activity in response to a particular external stimulus, named evoked potential. The term "evoked" indicates that, for any external sensory stimulation as light flash, sound, tactile sensation, the brain responds with a specific wave, characterized by a particular latency, amplitude, and polarity. If the activation of specific cognitive functions of the patient is required, these recorded potentials are dependent on the information content of the stimulus, and appear only when the subject pays attention to it. In this case the recorded potentials are Event-Related potentials (ERPs) [4]. The study of ERPs aims to understand how cognitive function to the stimulus is enhanced in the potential generated by the brain. So, ERPs can be reliably measured using EEG. However, the EEG reflects many thousands of simultaneously ongoing neuronal processes, and often is difficult to identify the response of the brain to a specific event in the ongoing EEG, because ERPs are characterized from a low voltage. In actual recording situations a number of single trials related to the presentation of the stimulus are averaged to obtain an estimate of the ERP. In this way noise and spontaneous EEG are cancelled, and the voltage response to the stimulus is enhanced clearly from the averaged out background. The problem of this procedure is that when the signal to noise ratio is very low, it is necessary to have a great number of single trials per patient, but this means long experimental times and the person could be stressed out. So, there is the necessity to use a method which improves the ability to detect the components of interest in the recorded EEGs. In literature there are proposed methods based on Independent component analysis (ICA), principal component analysis (PCA) and Discrete Wavelet Transform (DWT) [5]. In particular it has been well showed as DWT allows to obtain an optimal resolution in the time and frequency domain [6] overcoming the limitations of the Fourier Transform (FT). FT decomposes the signal into its sinusoidal constituents at different frequencies. So by applying FT on EEG signal, it is possible to quantify the brain activity for each frequency. However, there are drawbacks related to FT, because in the passage from time domain to frequency domain the time information is lost, and it is difficult to determine when a specific event occurs. DWT overcomes this problem and it allows to obtain a good resolution in time and frequency thanks also to the fact it doesn't require the stationarity of the signal. A limitation of DWT is in the choice of the waveform to carry out

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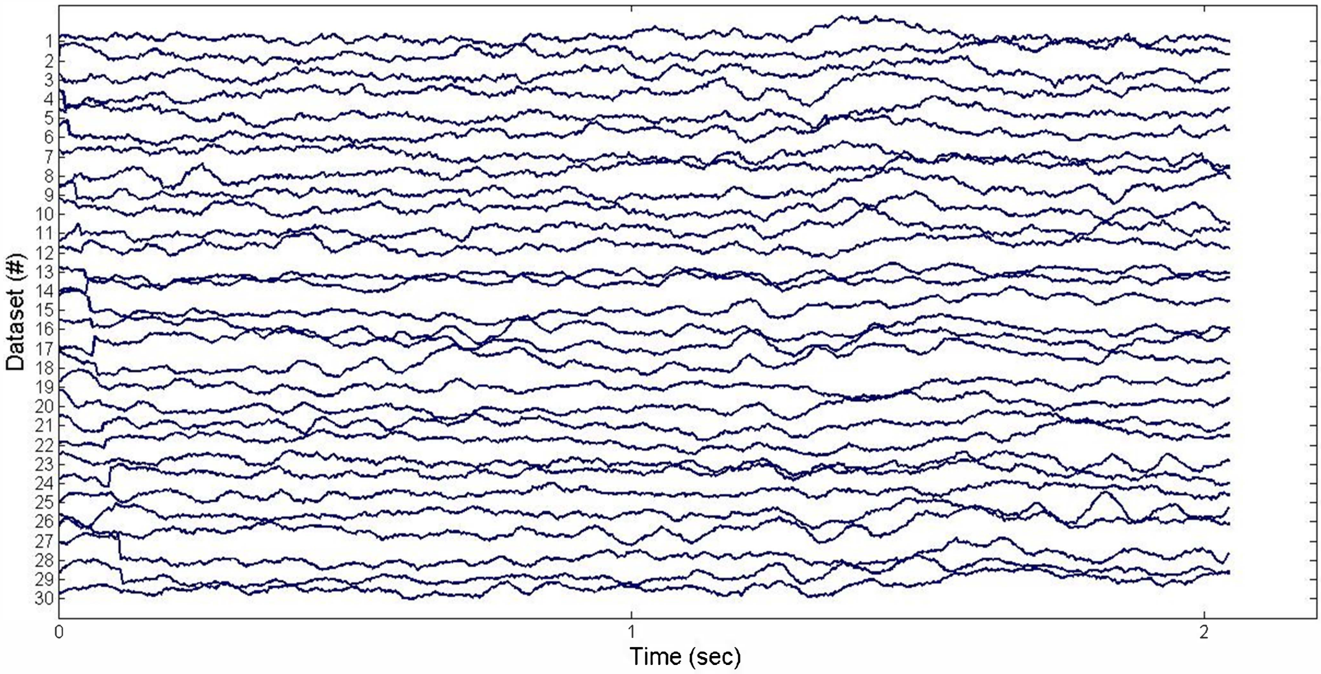

Fig. 1. Dataset of EEG signal for each trial

the analysis of the entire signal and to identify the level of decomposition to reach in order to extract the information of interest [7]. In this work Empirical Mode Decomposition (EMD) is used. It is a method that has been used to analyze data in diverse contexts, and in biosignal analysis too [7,8]. It is well suited to analyze non-stationary and non-linear signals like the EEGs. By using EMD, the original signal is decomposed as a linear combination of intrinsic oscillatory modes, called Intrinsic Mode Functions (IFMs). It allows to overcome the limitations of DWT because the basis used in the analysis is generated by the same analyzed signal. So we use this method to extract the VEPs components in EEG signal.

II. VEPs Dataset

In order to study the ability of the method to identify the Visually Evoked Potentials (VEPs), the EEG database available in [9] has been taken into consideration. As reported in [10], 30 VEPs (Fig.1) from one normal subject were obtained by using a checkerboard light pattern, with two visual stimuli occurred in according to oddball paradigm: 75% of the stimuli were the so-called "non-target" and the other 25% were the deviant stimuli or "target". The subject ignored the non-target and responded to the target ones.

Evoked potentials are defined as changes in ongoing EEG. These changes must be observed in different frequency bands upon the applied stimulus. They are related to different sensory and cognitive process, and it is possible to observe their contribution in different frequency bands (Fig.2).

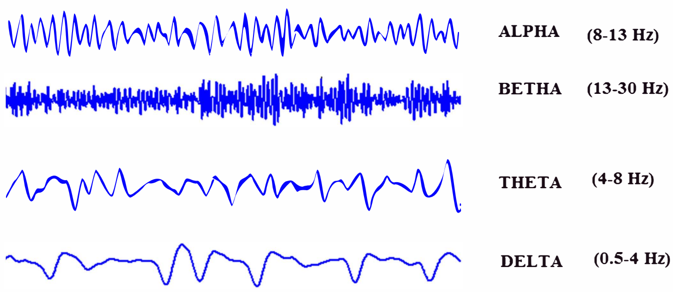

Fig. 2.Frequency band related normal EEG activity

In the considered dataset, EEGs were recorded from the left occipital electrode (O1), that is the electrode more near to the visual primary sensory area, connected to the earlobes reference. The data were acquired with a sampling frequency of 250 Hz, and pre-filtered in the range 0.1-70 Hz. So we have 256 pre- and 256 post-stimulation for each set of data containing a VEP component. Two evoked responses can be observed with this paradigm, a positive peak at about 100 ms after stimulation (P100) followed by a negative peak (N200) that appear both upon non-target and target stimuli, and a positive peak at about 400–500 ms after stimulation (P300) related to the cognitive process of recognizing the stimuli as deviant. In dataset showed in Fig.1, VEPs are difficult to detect due to their low amplitude, and so they are hided from background EEG activity. So, we demonstrate as EMD is suited to identify the P100-N200-P300 responses. In particular, the identification of the P300 component is very interesting because it is related to recognition processes, capability to make a decision, attention and memory updating. In different cognitive pathologies as depression, dementia, the P300 response can prove abnormal from calculation of its latency that is the time elapsed between the stimulus and the point of maximum positive amplitude within of the temporal considered window.

III. Empirical Mode Decomposition

Empirical Mode Decomposition (EMD) is a method proposed by Huang et al [11] that can be applied to study the nonlinear and non-stationary properties of a time series. EMD method separates the time-series into intrinsic oscillations by using local temporal and structural characteristics of the data. The starting point of EMD is to estimate locally a signal as a sum of a local trend and a local detail: the local trend is the low frequency part in the signal, while the local detail is the high frequency part [8]. The high frequency part is called Intrinsic Mode Function (IMF), and the low frequency part is the residual.

Considering an arbitrary signal *x(t)*, IMFs can be extracted in the following way:

- Identify all extrema (maxima and minima) of *x(t)*;
- Generate the upper and lower envelope ($e_{min}(t)$, $e_{max}(t)$) by interpolation of the maxima and minima points with a cubic spline;
- Compute the mean $m_1(t) = (e_{min}(t)+e_{max}(t))/2$;
- Extract the first component $h_1(t) = x(t)-m_1(t)$;

In Fig.3 the application of EMD for a generic signal is depicted.

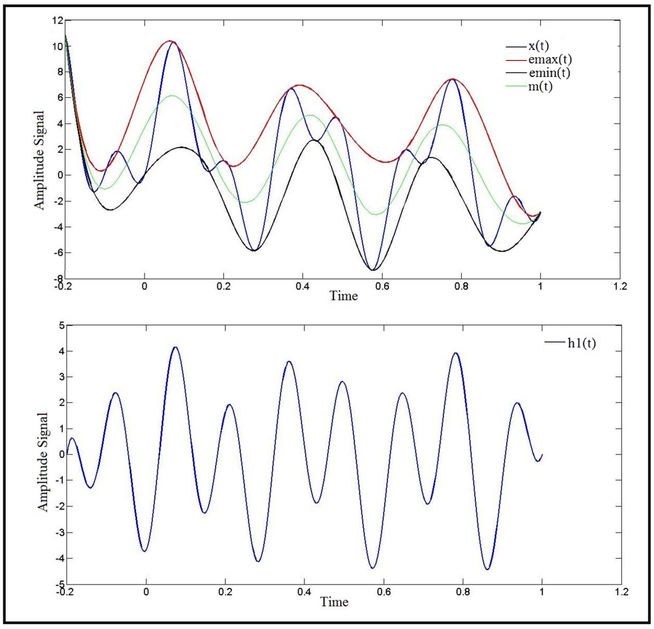

Fig. 3. Empirical Mode Decomposition of a generic signal

Ideally, $h_1(t)$ should satisfy the definition of IMF, since for the way in which it has been constructed it should be symmetric and has all the maximum points positive and the ones of minimum negative. So the described process should be iterated more times to obtain an IMF, and in this second step $h_1(t)$ is the new signal on which EDM is applied.

After k times, $h_{1k}(t)=c_1$ is define as IMF, and this is the faster oscillation mode present in the data. It is separated from the data as reported in Eq.(1):

$$r_1(t) = x(t) - c_1(t) \qquad (1)$$

Since in general the residue r_1 still contains oscillations of period more long, it is treated as the new signal and subjected at the same aforementioned procedure, until the residue becomes a function without a point of maximum and minimum. At the end of the decomposition process, the EMD method expresses the signal *x(t)* as the sum of a finite number of IMFs and a final residual:

$$x(t) = \sum_{j=1}^{n} c_j + r_n \qquad (2)$$

IV. Results

EMD method is applied on the average signal, that is obtained from the mean of 30 recorded trials and shown in Fig.1. In Fig.4 the calculated IFMs are reported, while in Fig.5 a comparison between the original average signal and the calculated residual related to the first three IMFs is shown.

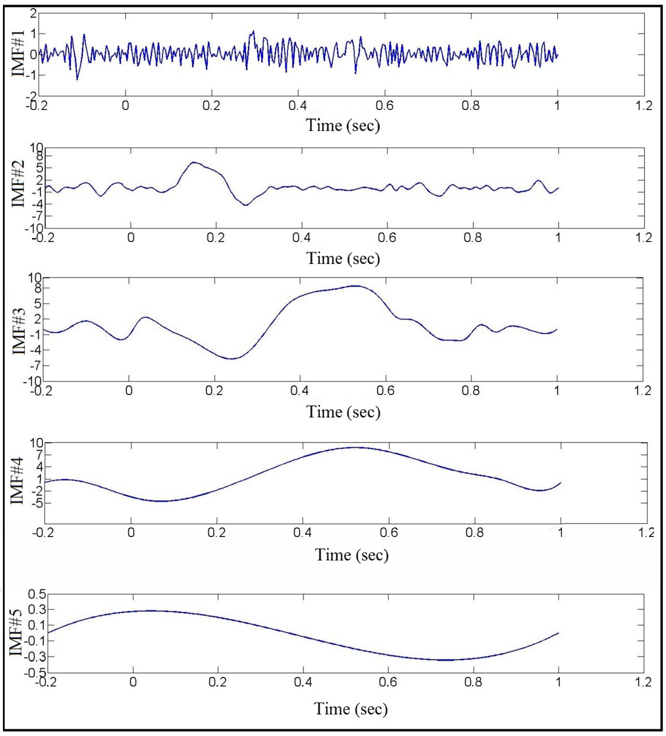

Fig. 4. IMFs obtained by the EMD applied on the average signal

The first IMF represents the faster oscillation mode present in the data, and so in the image at the top in Fig.5, the reconstructed signal (red line) is the denoising signal for the average signal under observation (blue line). In the second IMF is possible to see the peaks around P100 and N200 response. In the second reconstructed signal in Fig.5, these components are removed. So, from IMF #2 it is possible to correlate the P100-N200 response with the instant in which it occurs. This contributions are more visible in the third calculated IMF, where there is also P300 at about 400-500 ms, which is subtracted from the residual signal as reported in the last image in Fig.5. Also in this case, it is possible to achieve important temporal information about P100-N200-P300 waves. In the fourth IMF is visible only the P300. IMF5 is irrelevant because the signal does not exhibit components of interest.

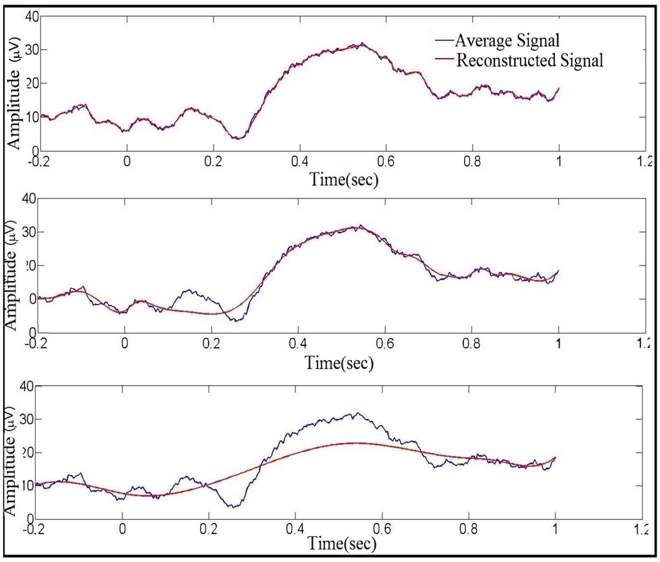

Fig. 5.Average signal and different residuals

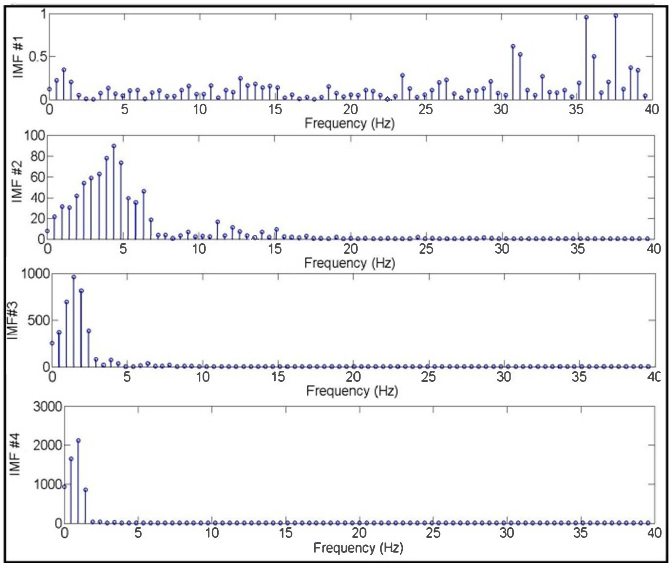

Fig. 6. PSD of calculated IMFs

Since Evoked potentials are defined as changes in ongoing EEG, changes must be observed in different frequency bands where the stimulus is applied. In fact, changes are related with different sensory and cognitive process. So it is possible to observe important contribution of VEPs in different frequency band. In Fig. 6 the Power Spectrum Density (PSD) for the IFMs shown in Fig.4 is reported. It is clear the decreasing of PSDs frequency components with increasing of the number of calculated IMFs. In Fig.7 the result obtained by DWT application is reported for a comparison with EMD method. In DWT the mother function used is sym6. D1-D6 are the detail signals, A6 is the last approximation. It is possible to see that D5 is correlated with P100-N200 waves, while A5 is correlated with P300.

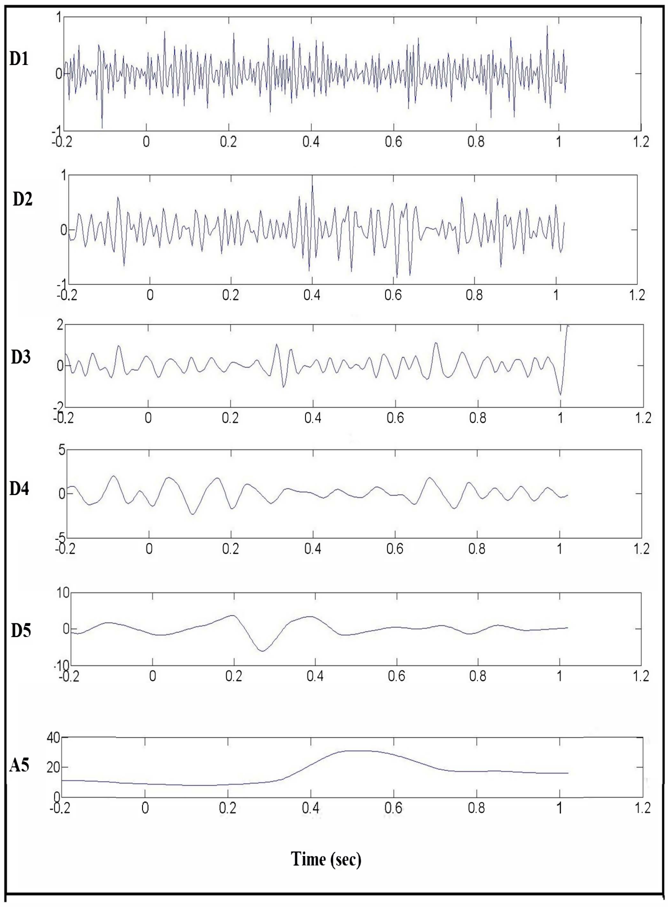

Fig. 7.Wavelet transform result

Therefore, preliminary observations can be made on the EMD method in comparison with DWT. EMD method similarly to the wavelet transform allows to give information about temporal instant in which a VEP occurs. However Wavelet Transform has a major complexity due to the necessity to choose the waveform to carry out the analysis of the entire signal and to identify the level of decomposition to reach and to obtain the information of interest. Instead, EMD method allows to overcome the limitations of DWT because the basis used in the analysis is generated by the same analyzed signal.

V. CONCLUSIONS

In this work EMD method has been successfully applied to evaluate Visual Evoked Potentials in single-channel EEG. VEPs are electrical potentials due to brief visual stimuli, and a their assessment is important to quantify the functional integrity of the optic pathway or to detect abnormalities related to cognitive pathologies. Abnormalities that affect the visual pathways can be detected in the analysis of VEPs, and so methods that allows to extract their components in accurate way are necessary. So Empirical Mode Decomposition (EMD) method is used to separate the EEG components and to detect VEPs. An evaluation in frequency domain is reported too. EMD has a good time and frequency resolution as Wavelet Transform method, but more simple to treat. More information may be obtained from a multivariate analysis, considering EEG signals acquired from multiple channels. In this sense, Multivariate Empirical Mode Decomposition can be useful [12]. The present research falls within a large one [13] that faces issues regarding epilepsy with signal processing problems [14]; it is wise to speak about epilepsies since each kind of them targets specific area of the brain and it involves other physiological functionalities [15] [16].

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