SOURCE LOCALIZATION OF BRAIN RHYTHMS BY EMPIRICAL MODE DECOMPOSITION AND SPATIAL NOTCH FILTERING

Delaram Jarchi, Vahid Abolghasemi and Saeid Sanei

Centre of Digital Signal Processing, School of Engineering, Cardiff University, Cardiff, Wales, UK
email: jarchid@cardiff.ac.uk

ABSTRACT

In this paper a new method for localization of sources of brain rhythmic activity is presented. The empirical mode decomposition (EMD) method is applied to an appropriate channel and one of the extracted intrinsic mode functions (IMFs) is selected as a reference signal for one of the brain rhythms. Then the spatial notch filter which is a constrained spatial filter based on a reference is applied to find the location of the desired rhythmic source. The use of EMD which is fully adaptive and data-driven method for analyzing nonstationary and nonlinear time series along with the recently developed spatial filter is a powerful method for localization of different rhythms in different frequency bands inside the brain. The method is applied on the simulated data and real BCI database. The results validate the effectiveness of the proposed method for localization of sources with different time-frequency signatures.

Index Terms— empirical mode decomposition (EMD), intrinsic mode functions (IMFs), spatial notch filter, reference.

1. INTRODUCTION

Electroencephalogram (EEG) is the electrical activity of the brain that gives us the possibility of studying brain functions with a high time resolution, although with a relatively modest spatial resolution [1]. Localization of ongoing oscillatory activity is important for establishing the normal spatial and spectral variation of cortical rhythmicity in the healthy human brain, and for characterizing abnormal changes induced. For estimation of the overall level of rhythmic activity, particularly when such a level is to be compared across different brain regions, localization of the generators of rhythmic activity is essential [2]. One method for localization of brain rhythmic activity is to combine frequency analysis with source localization methods [3],[4]. Based on this model the spatial distribution of the activity in a certain frequency band needs to be studied. Therefore, potential maps can be constructed for each frequency point using Fourier transform, and these potential maps can be subsequently used for source localization algorithms. This method, called “FFT dipole approximation” [3]. The shortcoming of this method is that Fourier spectral analysis is a full description of the dynamics only if the underlying system is linear. Moreover Fourier spectrum defines uniform harmonic components globally. Therefore, it requires many additional harmonic components to simulate nonuniform data. One approach has been synthesizing a signal that only contains the target time-frequency components of interest, and then apply a single-dipole localization procedure to this synthesized signal [5]. It is reported that this approach is tedious and in some cases is computationally intensive [6]. Another approach is time-frequency multiple signal classification (MUSIC) algorithm [6]. In this model the locations of neural sources are estimated from the corresponding time-frequency region of interest. In the proposed algorithm, quadratic time-frequency representations are used to provide better performance in comparison with the linear representations such as the well-known short-time Fourier transform (STFT) and the wavelet transform. The goal of the this method is to localize a source for a time-frequency region of interest.

In this paper we propose a new method for localization of brain rhythmic activity using the EMD [7] and our recently developed spatial notch filter [8]. Here, we seek to localize brain rhythms using the EMD algorithm in order to localize an oscillation inside the brain. EMD is a fully adaptive and data-driven method for analyzing nonstationary and nonlinear time series. In the proposed method first the EMD as a signal-dependent decomposition method is applied to one channel of the EEG time series to decompose it to waveforms modulated in amplitude and frequency. The iterative extraction of these components called intrinsic mode functions (IMFs), is based on the local representation of the signal as sum of a local oscillating component and a local trend. The IMFs can be considered as the reference signals for the brain rhythmic activities. The spatial notch filter is then applied to the EEG data considering the resulted reference signal. The output of the spatial notch filter is minimized in the location of the desired source. As long as the spatial notch filter is tuned to a pre-determined reference signal as input, there is no need to specify the number of brain sources.

The simulated results indicate that this method has the ability of correct localization of the brain rhythms even in low SNRs when the reference signal obtained by the EMD method is not exact. One important issue is selecting the appropriate channel which best approximates the reference signal for a certain brain rhythm. If the EMD is performed on most relevant channels, the algorithm will lead to accurate localization of the corresponding sources. Then, a real data for BCI application is selected to localize the well-known mu rhythm in the brain.

The remainder of the paper is structured as follows. In section 2 the spatial notch filter is described. Then, in section 3 the EMD method is briefly explained and in section 4, the source localization approach is described. In section 5 the results of applying the proposed method on both simulated data and real data are provided. Finally, section 6 concludes the paper.

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2. SPATIAL NOTCH FILTER

The new developed spatial notch filter is based on minimizing the distance between the reference signal and a filtered version of the EEG including the spatial information of the brain sources. The sources are modeled as current dipoles and their propagation to the sensors is mathematically described by an appropriate forward model [9],[10]. Consider the EEG signal as an $n \times T$ matrix - $\mathbf{X}$, where n is the number of electrodes and T is the length of the signals in terms of time samples

$$\mathbf{X} = \mathbf{HMS} + \mathbf{N} = \sum_{j=1}^{m} (\mathbf{H}_j \mathbf{m}_j \mathbf{s}_j) + \mathbf{N} \tag{1}$$

The term $\mathbf{HMS} + \mathbf{N}$ is the matrix form of the model and $\mathbf{H}$ is an $n \times 3m$ matrix describing the forward mixing model of the m sources to the n electrodes. $\mathbf{H}$ is further decomposed into m matrices $\mathbf{H}_j$ as

$$\mathbf{H} = [\mathbf{H}_1 ... \mathbf{H}_j ... \mathbf{H}_m] \tag{2}$$

where $\mathbf{H}_j$ is an $n \times 3$ matrix whose each column describes the potential at the electrodes due to the jth dipole for each of the three orthogonal orientations and $\mathbf{m}_j$ is a 3×1 vector describing the orientation of the jth dipole. For example, the first column of $\mathbf{H}_j$ describes the forward model of the x component of the jth dipole when the y and z components are zero, where x,y and z refer to the spatial coordinates. and $\mathbf{s}_j$, which is a $1 \times T$ vector, is the time course of the jth dipole and $\mathbf{N}$ is the combination of the measurement noise and the modeling error. The constrained problem of the spatial notch filter is defined as

$$min \quad f_d(\boldsymbol{w}) \quad subject\ to \quad f_c(\boldsymbol{w}) = 0 \tag{3}$$

where $f_d(\boldsymbol{w})$ is the Euclidean distance between the reference signal and the filtered EEG and $f_c(\boldsymbol{w})$ is a constrained function which puts a null in a spatial location p [8];

$$\begin{aligned} f_d(\boldsymbol{w}) &= \|\mathbf{r} - \boldsymbol{w}^T(X)\|_2^2 \\ f_c(\boldsymbol{w}) &= \boldsymbol{w}^T H(p) = 0 \end{aligned} \tag{4}$$

where $\boldsymbol{w}$ refers to the filter for extracting the desired source and $\mathbf{r}$ is the reference signal corresponding to the desired source. The constrained problem can be converted to an unconstrained optimization procedure by using Lagrange multipliers. Therefore, we can have the following equation:

$$\mathbf{F}(\boldsymbol{w}) = f_d(\boldsymbol{w}) + f_c(\boldsymbol{w})\kappa = \|\mathbf{r} - \boldsymbol{w}^T(X)\|_2^2 + \boldsymbol{w}^T H(p)\kappa \tag{5}$$

where κ is a 3×1 vector of Lagrange multipliers. After solving the above equation (by minimizing its gradient with respect to $\boldsymbol{w}$) the filter $\boldsymbol{w}$ will be obtained as [8]

$$\boldsymbol{w}^T = (\mathbf{r}X^T - \mathbf{r}X^T C_x^{-1} H(p)(H(p)^T C_x^{-1} H(p))H(p)^T)C_x^{-1} \tag{6}$$

where $C_x = XX^T$ is the covariance matrix of X. Based on this model, we have a beamformer which puts a null in the location of a source and then tries to find the desired source in other places which best matches the reference signal. In the case that beamformer has put the null in the location of the desired source then it fails to find such a match and the filter $\boldsymbol{w}$ returns zero. Therefore, when the filter output is zero or close to zero it means the exact source location is found.

3. EMPIRICAL MODE DECOMPOSITION

EMD [7] is a nonlinear technique to adaptively represent nonstationary signals as sum of their IMFs. EMD considers the oscillations in signals at a very local level. Each resulted IMF by the EMD method satisfies two basic conditions: (i) in the complete data set, the number of extrema and the number of zero crossings must be the same or differ at most by one, (ii) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. The EMD algorithm [11] for the signal $z(t)$ can be summarized as follows:

1. *Set* $g_1(t) = z(t)$
2. *Detect the extrema (both maxima and minima) of* $g_1(t)$
3. *Generate the upper and lower envelopes* $e_m(t)$ *and* $e_l(t)$ *respectively by connecting the maxima and minima separately with cubic spline interpolation*
4. *Determine the local mean as:* $m(t) = \frac{e_m(t)+e_l(t)}{2}$
5. *IMF should have zero local mean; subtract m(t) from the original signal as:* $g_1(t) = g_1(t) - m(t)$
6. *Decide whether* $g_1(t)$ *is an IMF or not by checking the two basic conditions as described above*
7. *Repeat step 2 to 6 and stop when an IMF* $g_1(t)$ *is obtained.*

Once the first IMF is derived, define $d_1(t) = g_1(t)$, which is the smallest temporal scale in $z(t)$. To find the rest of the IMFs, generate the residue $r_1(t)$ of the data by subtracting $d_1(t)$ from the signal as: $r_1(t) = z(t) - d_1(t)$. $r_1(t)$ is treated as the new data and subjected to the same sifting process as described above. The sifting process is continued until the final residue is a constant, monotonic function, or a function with only maxima and one minima from which no more IMF can be derived. At the end of the decomposition the signal $z(t)$ is represented as:

$$z(t) = \sum_{p=1}^{M} d_p(t) + r_M(t) \tag{7}$$

where M is the number of IMFs and $r_M(t)$ is the final residue. The EMD algorithm is applied to one channel of EEG data to decompose it to different brain rhythms. One of the selected IMFs can be used as a reference signal for one of the rhythms inside the brain.

4. SOURCE LOCALIZATION APPROACH

The new method for localization of brain oscillatory activities is a two step procedure. In the first step, the EMD method is applied to one channel of the EEG data to decompose it into oscillations that are orthogonal to each other. One advantage is that only one channel is required to obtain different brain rhythms. However, the selection of the best channel for a specific rhythm may require some prior knowledge. After applying the EMD, we may have several oscillations in a specified frequency band. In this case, first we are able to approximate a brain rhythm inside the brain using the EMD algorithm, then we can have a reference signal for one brain rhythm obtained by the EMD that can be subjected to the spatial notch filter. The selected IMF obtained from the EMD can be considered as the reference signal **r** in equation (6) to perform the localization. Therefore, a distinct foci for any oscillation inside the brain can be found. This is important for different functional states where a number of oscillations in distinct locations of the brain are dominant and active.

5. EXPERIMENTAL RESULTS

To show the effectiveness of the proposed localization method, this method is applied to both simulated data and real data. what follows is the description of the simulated data and real data and the results of applying the localization method to both datasets.

5.1 Simulated Data

Four frequency and amplitude modulated sine waves that belong to four different frequency bands have been generated. A forward model has been obtained using the BrainStorm software [12]. We have used a three layer spherical head model with conductivities of 0.33, 0.0042, 0.33 $\mu S/cm$, for scalp, skull, and brain, respectively. The generated signals have been placed in different locations inside the brain. The location for alpha, beta, theta and delta rhythms are shown in Fig. 1. Using the generated signals and the forward model and by assigning the location and moment for each source signal, the mixture EEG signals in 25 channels are generated using equation (1). Then the Gaussian noise is added to all the channels. We have applied the EMD to different EEG channels and for every channel each resulted IMF is considered as the reference signal **r** to be used in spatial notch filter formula. Therefore, using the reference signal **r** obtained by EMD, the spatial notch filter is applied to give the location of the desired signal. Table 1 shows the error of localization using the IMF which corresponds to the desired brain rhythm obtained from different channels. For some channels, the zero error is obtained. Then the selection of the best channel is essential when dealing with the real data. Our experiment showed that the best channel is the channel nearest to the source considering the orientation and moment of the source and also the channel that its resulted IMF has continuous instantaneous frequency. The original simulated brain rhythms and the extracted brain rhythms using EMD obtained from some of the channels are shown in Fig. 2. Table 2 contains the correlation coefficient of the resulted IMF as reference and the original signal. In general the reference does not need to be exact and for the case that the correlation coefficient is high, the chance of having the localization error of zero or close to zero is high.

5.2 Real data

The real data used in this paper is the BCI competition data [13]. The recording was made using BrainAmp MR plus amplifiers and a Ag/AgCl electrode cap. Signals from 59 EEG positions were measured that were most densely distributed over sensorimotor areas. Signals were bandpass filtered between 0.05 and 200 Hz and sampled at 1000 Hz with 16 bit (0.1 uV) quantization. Here a version of the data that is downsampled to 100 Hz is used. The dataset is recorded from healthy subjects. In the whole session motor imagery has been performed without feedback. Based on the available EEG data, the corresponding forward model has been created. The head model is the same as the simulated data but we increased the number of grid points inside the brain to have a better estimation. As a result, the limit of the x,y and z axis is increased in the read data and it is evident in Fig. 4. The EMD is applied on the C3 channel to decompose it to several IMFs. One of the extracted IMFs in the alpha frequency band is chosen and is shown in Fig. 3. The suppression of mu rhythm during the motor imaginary task can be seen in this IMF. This IMF is selected as the reference signal for mu rhythm. Then, the spatial notch filter is applied providing the reference signal for the mu rhythm. The result of localization of mu rhythm is shown is Fig. 4. This is consistent with previous finding about the location of mu rhythm [6]. Therefore, the EMD algorithm along with the spatial notch filter has the ability of localizing different brain rhythms inside the brain.

6. DISCUSSION AND CONCLUSION

In this paper a new method for localization of different brain rhythms inside the brain is proposed. The method is a two step algorithm which first uses EMD algorithm to obtain brain rhythms from only one channel. Then the spatial notch filter is applied to find the location of the extracted brain rhythm from the multi-channel EEG. The selection of the best channel for extracting the appropriate brain rhythm is crucial. To achieve that the prior knowledge about different brain rhythm can be useful. Also a clustering algorithm can be applied to the result of localization obtained from several close electrodes to give the approximate location of the rhythm in the case that is not clear which channel is the best for localization. The method can be applied to different real data such as mental fatigue data to see whether brain rhythms have different locations in different mental states. Indeed, the beamformer performance can be improved by adding more null constraints to suppress the effect of the correlated sources.

REFERENCES

[1] S. Sanei and J. Chambers, *EEG signal Processing*, John Wiley and Sons, 2007.

[2] M. Liljestrfm, J. Kujala, O. Jensen, and R. Salmelin, "Neuromagnetic localization of rhythmic activity in the human brain: a comparison of three methods," *NeuroImage*, vol. 25, pp. 734–745, 2005.

[3] C. M. Michel, D. Lehmann, and B. Henggeler, "Localization of the sources of eeg delta, theta, alpha and beta frequency bands using the fft dipole approximation," *Electroenceph. Clin. Neurophysiol*, vol. 82, pp. 38–44, 1992.

[4] C. M. Michel, M. Koukkou, and D. Lehmann, "Eeg reactivity in high and low symptomatic schizophrenics, using source modeling in the frequency domain," *Brain Topog*, vol. 5, pp. 389–394, 1993.

[5] M. Sun, S. Qian, X. Yan, S. B. Baumann, X. G. Xia, R. E. Dahl, D. Ryan, and R. J. Sclabassi, "Localizing functional activity in the brain through time-frequency analysis and synthesis of the eeg," *in* Proc. IEEE, vol. 84, pp. 1302–1311, 1996.

[6] K. Sekihara, S. S. Nagarajan, D. Poeppel, S. Miyauchi, N. Fujimaki, H. Koizumi, and Y. Miyashita, "Estimating neural sources from each time-frequency component of magnetoencephalographic data," *IEEE Trans. Biomed.*, vol. 47, pp. 642–653, 2000.

[7] N. E. Huang, Z. Shen, S. R. Long, M. C. Wu, H. H. Shih, Q. Zheng, N. C. Yen, C. C. Tung, and H. H. Liu, "The empirical mode decomposition and hilbert spectrum for nonlinear and non-stationary time series analysis," *Proc Roy Soc London A*, vol. 454, pp. 903–995, 1998.

[8] L. Spyrou and S. Sanei, "Source localization of event-related potentials incorporating spatial notch filters," *IEEE Trans. Biomed.*, vol. 55, pp. 2232–2239, 2008.

[9] J. Sarvas, "Basic mathematical and electromagnetic concepts of the biomagnetic inverse problem," *Phys. Med. Biol.*, vol. 32, pp. 11–22, 1987.

[10] P. H. Schimpf, J. Haueisen, C. Ramon, and H. Nowak, "Realistic computer modeling of electric and magnetic fields of human head and torso," *Parallel Comput.*, vol. 24, pp. 1433–1460, 1998.

[11] P. Flandrin, G. Rilling, and P. Goncalves, "Empirical mode decomposition as a filter bank," *IEEE Sig. Proc. Letters*, vol. 11, pp. 112–114, 2004.

[12] *BrainStorm, Matlab Toolbox [Online]. Available: http://neuroimage. usc.edu/brainstorm/.*

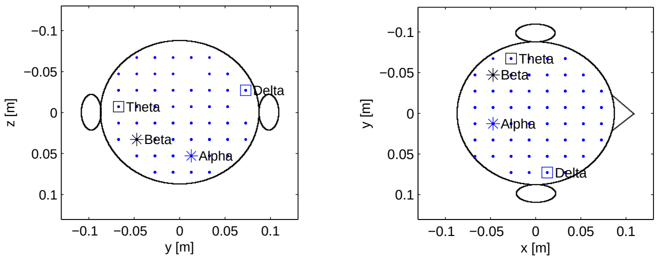
[13] B. Blankertz, G. Dornhege, M. Krauledat, K. R. Mller, and G. Curio, "The non-invasive berlin brain-computer interface: Fast acquisition of effective performance in untrained subjects," *NeuroImage*, vol. 37, pp. 539–550, 2007.

Table 1. Localization error of brain rhythms in which the reference is obtained from different channels

	Beta	Alpha	Theta
Ch#1	0.0693	0.0632	0.0400
Ch#2	0.0283	0.0400	0.0283
Ch#3	0.0346	0.0400	0.0283
Ch#4	0.0283	0.0400	0
Ch#5	0.0200	0.0400	0.0400
Ch#6	0.0283	0	0.0400
Ch#7	0.0283	0.0283	0.0400
Ch#8	0.0283	0	0
Ch#9	0.0200	0.0825	0
Ch#10	0	0.0400	0.0490
Ch#11	0.0283	0.0825	0
Ch#12	0.1562	0	0
Ch#13	0.0283	0	0
Ch#14	0.0283	0.0400	0.0283
Ch#15	0.0283	0.0400	0
Ch#16	0.0200	0.0283	0.0283
Ch#17	0.0283	0.0825	0.0283
Ch#18	0.0200	0.0400	0.0632
Ch#19	0.0283	0.0825	0.0283
Ch#20	0.0200	0.0447	0.0283
Ch#21	0.0283	0.0283	0.0490
Ch#22	0.1039	0.0447	0.0283
Ch#23	0.0283	0	0.0400
Ch#24	0.0200	0	0
Ch#25	0.0490	0.0200	0.0283

Table 2. Correlation coefficients of the resulted IMF selected as reference and the original source

	Beta	Alpha	Theta
Ch#1	0.6838	0.5228	0.5106
Ch#2	0.7037	0.6651	0.5240
Ch#3	0.7508	0.5915	0.5115
Ch#4	0.6893	0.5895	0.5422
Ch#5	0.7597	0.6310	0.5405
Ch#6	0.7982	0.8139	0.6221
Ch#7	0.8501	0.7290	0.5146
Ch#8	0.7919	0.7924	0.7334
Ch#9	0.8032	0.7183	0.7168
Ch#10	0.6732	0.5995	0.4619
Ch#11	0.8829	0.6189	0.6177
Ch#12	0.7023	0.7216	0.6403
Ch#13	0.8025	0.6873	0.5817
Ch#14	0.6854	0.6899	0.6110
Ch#15	0.8458	0.7113	0.6625
Ch#16	0.6938	0.6975	0.7479
Ch#17	0.8700	0.6515	0.6763
Ch#18	0.6653	0.6121	0.4393
Ch#19	0.7876	0.5117	0.5511
Ch#20	0.7241	0.7872	0.5509
Ch#21	0.8157	0.7277	0.5575
Ch#22	0.5712	0.5552	0.4320
Ch#23	0.8855	0.5915	0.5165
Ch#24	0.7292	0.7686	0.7503
Ch#25	0.8501	0.6450	0.5666



(a) (b)

Fig. 1. The location of brain rhythms inside the brain; (a) coronal view, (b) transverse view for the simulated data.

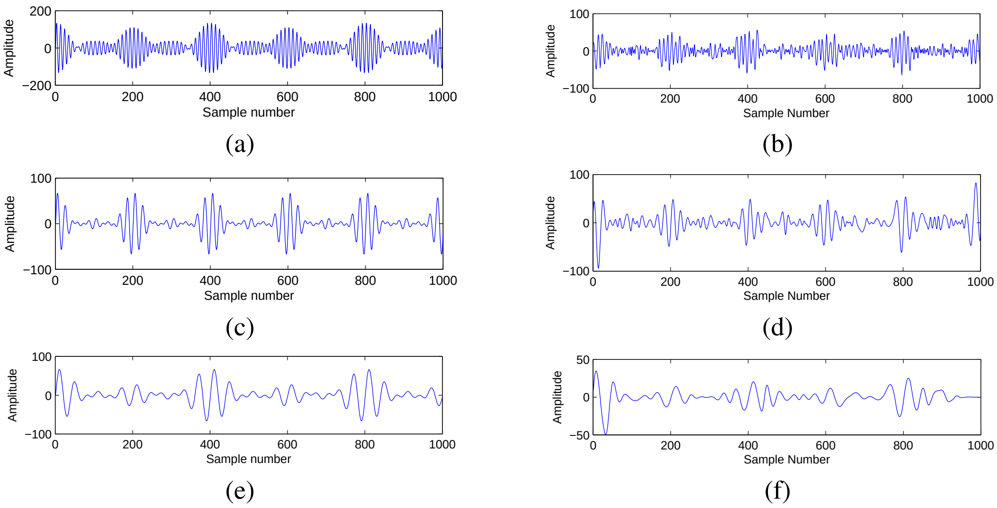
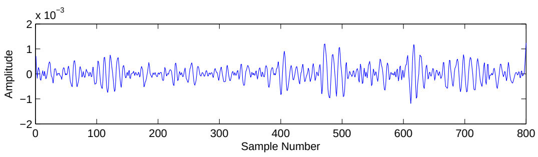
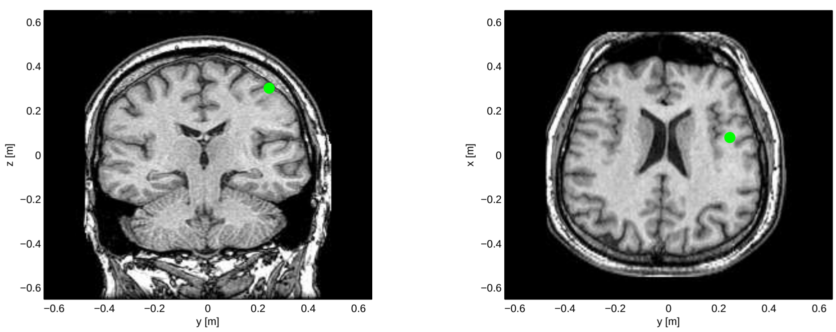


Fig. 2. Original simulated sources; (a) beta rhythm, (c) alpha rhythm, (e) theta rhythm, and the extracted sources using EMD; (b) Extracted beta rhythm from channel 10, (d) Extracted alpha rhythm from channel 6, (f) Extracted theta rhythm from channel 24, SNR = 7.8775.



(a)

Fig. 3. The Extracted IMF using the EMD algorithm.



(a) (b)

Fig. 4. The location of selected IMF as mu rhythm inside the brain; (a) coronal view, (b) transverse view.