On the Detection of the Number of Independent Sources from Scalp EEGs

X. Bai[1], Bin He[1]

[1]Department of Biomedical Engineering, University of Minnesota, MN, USA

Abstract— **Many source localization strategies need the number of sources as the input parameter (e.g., spatio-temporal dipole fitting, the multiple signal classification and the first principal vectors). In this study, an information criterion method based on the spatio-temporal signal model is presented, which can estimate the number of independent sources from measured signals. Computer simulations are conducted to evaluate the effects of various parameters on the estimation of source number. A three-concentric-sphere head model is used to represent the head volume conductor. Two kinds of signal sources, i.e. the damped sinusoid sources and sinusoid sources within two separated frequency bands are used to simulate the oscillation characteristic of epileptic sources for ictal and interictal spikes. The present results suggest that the present method can estimate the number of sources from the EEG measurements for the two kinds of signal sources. For five sources, the best performance of estimation for damped sinusoid and sinusoid sources are 90% and 98% under 20% additive non-ideal noise, respectively. It is also found that the different penalty functions used in the information criterion method could have substantial influence on the estimation accuracy for the non-ideal noise.**

Keywords—**Spatio-temporal model, information criterion, high resolution EEG, brain mapping**

I. INTRODUCTION

The reconstruction of brain activity from measured electroencephalograms (EEGs) is receiving wide interest [1]. Many inverse methods have been developed to reconstruct the brain activity, such as the spatio-temporal dipole localization [2], the multiple signal classification (MUSIC) [3] and the first principal vectors (FINES) [4]. However, in these methods, precise estimate of the sources may be obtained only if the number of sources is correctly determined. Currently, researchers must assume the number of independent sources.

Uijen and van Oosterm [5] proposed the information criterion method and the threshold method to detect the number of independent signals in Multilead ECGs. They showed that the information criterion method is superior in detecting the number of signal components. Knösche et al. [6] used the information criterion method to determine the number of independent sources of scalp EEGs. Nine kinds of information criteria functions were used to estimate the number of independent sources. And the noise, electrode number and the number of time points were also considered in the simulation. However, the computational simulation only considered an ideal source activity. On the other hand, the influence of the penalty function on the identification has not been addressed.

In the present study, we present the information criterion (IC) method to estimate the number of sources for two kinds of signal sources. The effects of the penalty functions, the noise and source activity on the identification of the number of sources are evaluated via numerical simulations.

II. METHODS

A. Information Criterion

The measured potential set recorded by M electrodes in the N time instant points can generally be described as

$$\mathbf{V} = \mathbf{AS} + \mathbf{N}. \tag{1}$$

where $\mathbf{V}$ is the $M \times N$ measurement matrix, $\mathbf{A}$ is a transfer matrix with M columns and K rows from the sources' strength to the measurements and it depends on the location of sources and electrodes, and the conductivity distribution of the head model, $\mathbf{S}$ is the $K \times N$ source strength matrix, $\mathbf{N}$ represents the additive noise, and K is the number of sources. The number of sources can be determined by analyzing the eigenvalues of the covariance matrix $\mathbf{R}$ of $\mathbf{V}$ **in Eq.** (1) by the IC method. The IC (IC_k) value can be expressed as follows:

$$IC_k = N(M-k)\log\frac{1}{M-k}\sum_{i=k+1}^{M}\lambda_i - N\sum_{i=k+1}^{M}\log\lambda_i + 2d(k,M)C(N), \tag{2}$$

where log(•) is the natural logarithm, λ_i is the i-th eigenvalue of $\mathbf{R}$, k is the number of assumed sources, and $d(k, M) = k(2M-k+1)/2$. According to the rule of the IC method, the number of sources with minimum IC is selected as the estimated number of sources. In 1969, AKAIKE firstly proposed the AIC, a statistic incorporating Kullback-Leibler information with the use of maximum likelihood principles and negative entropy. Different penalty functions based on AIC have been reported [7]. In the present study, the penalty function $C(N)$ can take one of the following five forms: 1) $C_1 = 2$; 2) $C_2 = 2\log(\log(N))$; 3) $C_3 = \log(N)$; 4) $C_4 = 2\log(N)$; 5) $C_5 = 3\log(N)$.

B. Computer Simulations

In the forward procedures of the simulations, a three-concentric-sphere model consisting of three compartments (with radii of 8.7 cm, 9.2 cm and 10 cm) was used to approximate the head volume conductor. The corresponding conductivity values (0.33s/m, 0.0165s/m, 0.33 s/m) for the various tissue types are adapted from Lai et al. [8]. The scalp potentials are assumed to be measured on the outermost sphere by a 128-electrode system. The number of the sources ranges from one to five in a row. For each set of the sources, 500 samples were generated. For all samples, the locations were generated randomly under the constraint that the distance between any two dipoles is larger than 1.0 cm. The orientations were generated randomly.

As each sample, the fixed sources are assumed based on the spatio-temporal model. The sampling rate is 2000 Hz and 200 temporal samples (=100 ms) are obtained in the forward simulation [9]. Here, two kinds of sources shown in Fig. 1 are used, i.e. the damped sinusoid sources and sinusoid sources within two separated frequency bands (10 Hz and 40 Hz). Both of them are intended to simulate the oscillation characteristic of epileptic sources for ictal and interictal spikes. Within each case, the non-ideal noise is added to the simulation data. Firstly, the white noise is obtained by adding noise of normal distribution at different levels (5%, 10%, 20%, 30% and 40%). The noise level is defined as a percentage ratio of the root mean square value of the noise to that of the potential data [4]. It is then multiplied by a $M \times M$ matrix $\mathbf{T}$. For the white noise mentioned above, this matrix is diagonal and its elements are uniformly 1. For the spatially correlated noise, the elements of $\mathbf{T}$ are $T_{ij} = 0.5/h$ for adjacent *i-th* and *j-th* electrodes, where h is the adjacent electrode number of the *i*-th electrode. When i is equal to j, $T_{ij} = 0.5$ and $T_{ij} = 0$ otherwise [6].

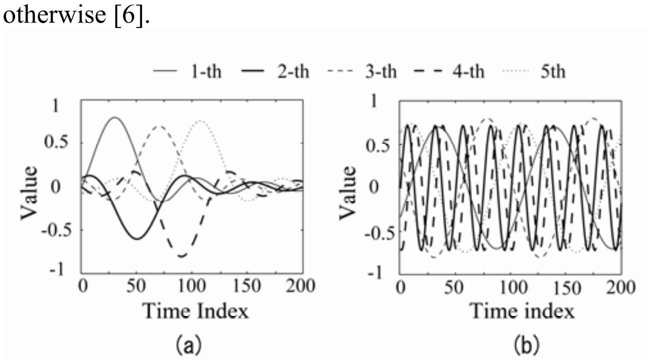

Fig. 1. Two source waveforms used in the present simulation.
(a) Case A: damped sinusoid waveforms, (b) Case B: sinusoid waveforms.

III. Results

A. Case A

At first, we investigated how the present method performs under 10% non-ideal noises. Fig. 2 (I) indicates that the accuracy of identification can be impacted by the different penalty functions for the non-ideal noise. With the penalty functions C_1 and C_2 we can not obtain the correct source number for the five-source cases. From the distribution of the five-source cases, C_3 yielded the highest identification accuracy, i.e., the detected source number in all samples is five. When the larger penalty functions (C_4 and C_5) are used, the detected source number in some samples is smaller than five. Therefore, it is important to use the suitable penalty function under the non-ideal noise.

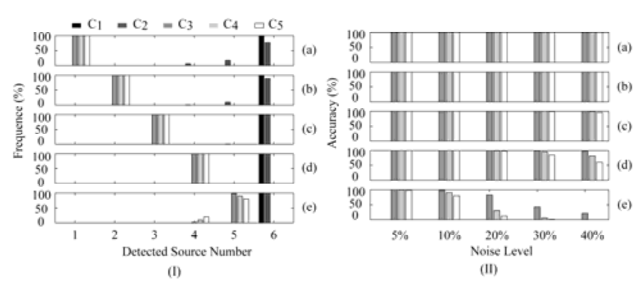

Fig. 2. The Identification results for Case A. (I) distribution of estimated source number for 10% non-ideal noise and (II) Accuracies of five cases with the proposed method. (a) one dipole case, (b) two dipoles case, (c) three dipoles case, (d) four dipoles case and (e) five dipoles case.

On the other hand, the noise level may affect the identification results and the selection of the penalty function. Fig. 2 (II) summarizes the accuracies of five-source cases under five noise levels, where the accuracy defined as the percentage of the correct estimation cases in all the samples. The simulation results indicate that the accuracies of identification are not influenced for one-, two- and three-source cases when the noise level increases. The accuracy of them is between 99% and 100%. However, the variance of noise level can impact the accuracy of four- and five-source cases. When the noise level is larger than 20%, the accuracies of five sources case are lower than 50% using C_3 under the non-ideal noise. For Case A, it can be concluded that C_3 is the optimal penalty function and can identify effectively up to five sources.

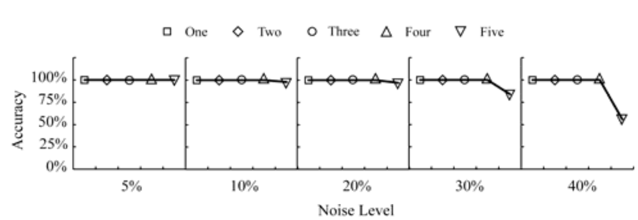

Fig. 3. Accuracies of five cases with C_3 for the non-ideal noise, Case B.

B. Case B

In the case of sinusoid waveforms, C_3 also provided the optimal performance. Fig. 3 summarizes accuracies with C_3. When the noise level is larger than 30%, the accuracies of five-source case are lower than 60% under the non-ideal noise.

IV. Discussion

In the present study, we use the IC method to estimate the number of independent sources in the spatio-temporal model. The main results of numerical simulations are as follows. Firstly, the choice of penalty functions in the IC method can significantly affect the identification accuracy for the non-ideal noise in all source cases and increase the ability of tolerating the non-ideal noise. By the simulation, the optimal penalty function can be determined, given the forward model and the electrode configuration. Secondly, the form of the time function also can affect the accuracy of identification substantially. According to the simulation results, we can estimate the number of sources up to five for the damped sinusoid sources and sinusoid sources. Lastly, we find that the optimal penalty function is C_3 for 128-electrode configuration. It has the best ability of tolerating the non-ideal noise. For the two kinds of the sources, the highest accuracies can be obtained by the present method.

ACKNOWLEDGMENT

This work was supported in part by NIH R01EB00178, and NSF BES-0411898.

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