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A Method for Two EEG Sources Localization by Combining BP Neural Networks with Nonlinear Least Square Method

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Abstract

EEG source localization is well known as an important inverse problem of electrophysiology. Usually there is no closed-form solution for this problem and it requires iterative techniques such as the Levenberg-Marquardt algorithm. However, the method requires long computing times, huge memory and large number of electrodes to avoid local minima. To overcome these problems, a method combining back propagation neural network (BPNN) with nonlinear least square method (NLS) is therefore proposed in this study. The new method shows how to estimate an approximate solution of the inverse problem by the BPNN method, and how to select the initial value of the NLS method due to the results of BPNN to obtain the optimum solution, where the problem is solved by POWELL iterative algorithm.

1 Introduction

Brain source localization using Electroencephalograms (EEG's) recorded from the scalp of the head is a classic example of an ill-posed problem in electrophysiology and widely used to make non-invasive estimates of the locations of sources of electrical activity in the human brain [1].

Localization of an electric dipole in the brain has a relatively long history since Brazier who first suggested a relation between scalp potential distributions and current sources in the human brain. A number of works in the last few decades have attempted to solve the EEG inverse problem by some methods and minimization algorithms such as Simplex Method and Marquardt algorithm [2]. In general, in order to obtain high localization accuracy from the EEG data, long time computer resource and huge computer memory should be requested. A direct method to compute source parameters from a voltage set measured on the scalp such as Moving Dipole [3], Dipole Tracing [4], etc., is therefore proposed.

In our previous studies, the back propagation neural networks (BPNN) was used to solve the inverse problem of electrophysiology [5][6]. The major advantage of the technique is that once a neural network is trained, it no longer requires iterations or access to sophisticated computers. Since no forward calculation is involved during actual use, any sophisticated head/source model can be used with equal ease irrespective of whether a simple analytical solution or a sophisticated finite element analysis is used. Furthermore, neural networks are capable of capturing the nonlinear dynamics of the source localization problem, while maintaining the noise robustness essential to EEG analysis.

The purpose of this research is to evaluate the method that localizes two sources in the brain by attached electrodes on the scalp. This problem can be solved by the BPNN method mentioned above. The accuracy may however be low comparing with the case of single dipole source localization, because the inverse functions to be installed in the neural networks are more complex. A method combining BPNN with NLS method is proposed here to overcome those problems, which satisfies all the requirements, and in this method the outputs of BPNN are used as an initial value of the NLS method.

2 Methods

The results reported in this paper are based on the following models commonly found in literature: (a) the human brain is represented by the three-concentric-shell model [7], and the biopotential sources are represented by current dipoles [7]. Each dipole is parameterized by its location vector **P** and the dipole moment vector **M**. The set of EEG measuring electrodes are place on the scalp according to the standard international 10/20 system, with a linked-ear reference.

In this study, we set the head model into two regions, the left region and the right region in order to avoid the influence of the distance between two dipoles. The head model can be shown in Fig.1. Two dipoles were put randomly in these two regions in order to get training patterns for BPNN.

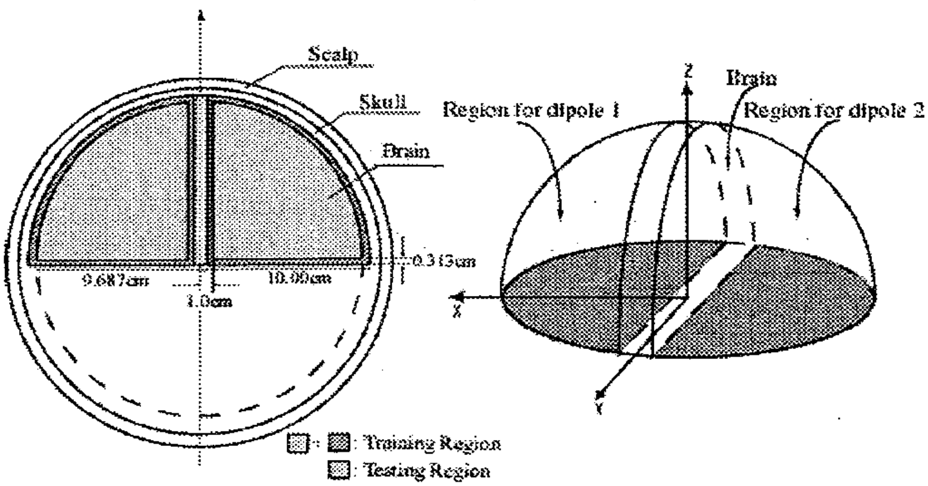


Fig. 1 The three-concentric shell head model

Once the source model and a head model have been assumed, the next step is to calculate the inverse solution for the location of the source in the model. Because BPNN can realize any inverse function easily, it is a reasonable method for our problem. BPNN also has the advantage that, once it has been trained, it can compute the outputs very fast. This method is therefore fast enough to satisfy the requirement of real time analysis. Because of these advantages of BPNN method, the method is used here for parameters estimation of two brain sources.

The architecture of the neural network used here is shown in Fig.2. If an EEG pattern is fed into the network, the output will be the position of the dipole, and dipole moment. Here, the network consists of four layers (an input layer, two hidden layers, and an output layer). There are 18 neurons to receive the potentials from 18 electrodes in the input layer, 73 neurons in each hidden layer. The network has also bias neurons with a constant output value of 1, to adjust the threshold of each neuron. The output layer just consists of one neuron indicating one of components of dipole position **P**, i.e., (x, y, z) or moment **M**, i.e., (M_x, M_y, M_z). The twelve same structure networks are therefore used in parallel for position and moment estimations. That is, the network makes use of the independence of twelve source parameters. Neurons in the input layer have a liner input-output function, while other neurons have a sigmoid function.

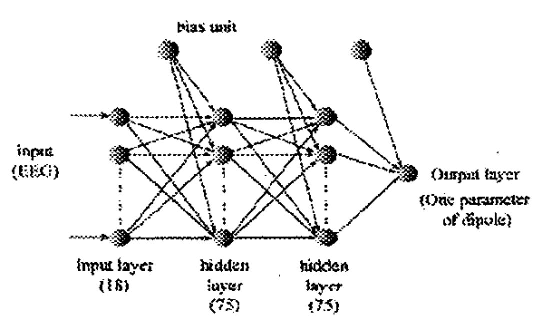


Fig.2. The structure of neural networks

To implement the inverse function, an error back propagation algorithm (BP algorithm) is used. The data pairs for training the networks are generated theoretically. 30,000 data pairs, obtained by putting the position and direction of each dipole randomly in the region shown in Fig.1, are used here for a training phase. In test phase, different 10,000 data pairs are prepared to test a function acquired by the networks. To avoid large error near the boundary of the regions in Fig.1, the regions in the training phase are taken about 5% larger than it in test region.

Considering the influence of the measurement noise, the error function J_{LS} can be expressed as:

$$J_{LS} = \varepsilon^T W^{-1} \varepsilon \qquad (1)$$

where ε is the noise vector between measurement value and calculation value. The covariance matrix W is given by $W = E\ \{\varepsilon \varepsilon^T\} = \sigma_\varepsilon^2 I$, where $E\ \{\bullet\}$ denotes the expected value of the argument, and I is identity matrix, σ_ε is the standard deviation of ε. Because the measurement noise can not be obtained in details and electrodes are assumed to be independent to each other, the noise may be considered as zero-mean and white noise, and therefore W is a n x n diagonal matrix. If we have a priori knowledge of covariance matrix of noise, Eq.(1) becomes the error function for the Least-Squares method with weight matrix W. However, since the knowledge is very difficult to be given, the residual value of last time iteration is used here as the weight matrix of current iteration. The goal is to find the set {P, M} that minimizes the error cost function J_{LS}.

To get the minimum error function J_{LS}, many iteration algorithms can be used, such as Direct-Search method, Steepest Decent method, Newton-Gauss method and so on. In this study, the POWELL iteration algorithm is used for minimizing the cost function. The POWELL iteration algorithm is very similar to the Levenberg-Marquardt method. It provides a fast way of iterative calculation.

If the initial value point of iteration algorithm is randomly selected, the result maybe not convergent or trapped in the local minim of J_{LS}, and always we need to restart of iteration routines. Here, the outputs of BPNN are used as the initial values of the iteration algorithm to ensure for getting convergent results quickly and precisely, and because of the usage of BPNN method, the problem becomes small-residue searching problem.

The system outline used in this study can be shown in Fig. 3.

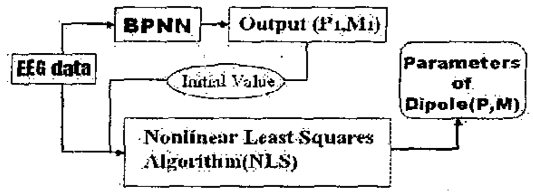


Fig. 3 The system outline for combining BPNN with NLS method used in this study.

3 Results and discussions

In our study, the estimation error in average is denoted as E_{rms}, where E_{rms} has the sense of a root-mean-square relative error $\varepsilon(\%)$ with 10,000 data pairs for test phase.

At first, how to decide the optimum size of neural networks is an important problem. It can influence the training time, estimation accuracy. In order to improve the estimate accuracy and reduce the burden of the network, also the relationship among the parameters can be considered as independent, twelve same structure networks are therefore used in this study whose outputs respond each parameter of dipole source. There is no certain rule for deciding the size of hidden layers and the number of neurons in each hidden layer. We can only choose the appropriate BPNN by series of experiments. In the experiments, various network structures are used and the network performance are compared in order to decide the most appropriate network structure. At the beginning, we consider the BPNN with only one hidden layer, which consists of 73 neurons. In the training phase, the maximum iterations number is set to 30000, and the mean square error goal is set to 0.3. Twelve networks did not reach the error goal when the maximum iterations number reached. The performance of the networks mentioned above is very bad. Obviously, the performance is far from satisfactory. In trying to get better results, we adopt the BPNN with two hidden layers, each consists of 73 neurons. Then the performance of BPNN with two hidden layers improved. We therefore concluded that the size of BPNN with two hidden layers and one output may be optimum.

For the localization accuracy based on the head model shown in Fig.1 with BPNN only, it gave the average position error of 8.7% and direction error of 2.16 degree respectively. Though the localization accuracy was not good while comparing with the case of single dipole source localization [6], it still examined the usefulness of BPNN for two dipole source localization.

To improve the estimation accuracy of two dipole source localization system, two different ways are investigated in this study. One considerable idea is to restrict the two dipoles in a smaller region for training and test phase using the BPNN method for some special applications, such as auditory source localization; another is to combine the BPNN method with Nonlinear Least-Squares method. Fig. 4 shows the restricted head model for the first idea. Here, the average position error of 5.6% and average direction error of 1.54 degree were obtained respectively from the simulation. The usefulness of this idea is very limited though it gives the small errors, because the approximated area of the sources cannot be known beforehand in general. Some other methods should be therefore considered in order to make the system more general.

localization. The error distribution of large number of dipole pairs in the localization region without noise by different methods using BPNN and combined system can be shown in Fig. 5. It can be easily concluded that the localization accuracy obtained from combined system is more precise

In order to prove that this system can get good results even in the worse condition, it is localized two dipoles here with 30% white noise theoretically since the real measurement noise strength can not be measured. The position error distribution is focused here since it is more important for clinical application than the direction component of the dipoles. The distribution is shown in Fig. 6.

Comparing both methods, the method combined the BPNN with the NLS gives the small average in both position and direction errors. Also the computation time of this method is less than 95ms for each pattern, so it is fast enough for real time localization. Because of these advantages of the system, it may be applied for clinical application.

In practical application, another main factor for influencing localization accuracy can not be ignored. It is the head model. Lots of researchers in the world are using real head model to make the source localization. Considering about the computing power and complexity, the three concentric-shell model is

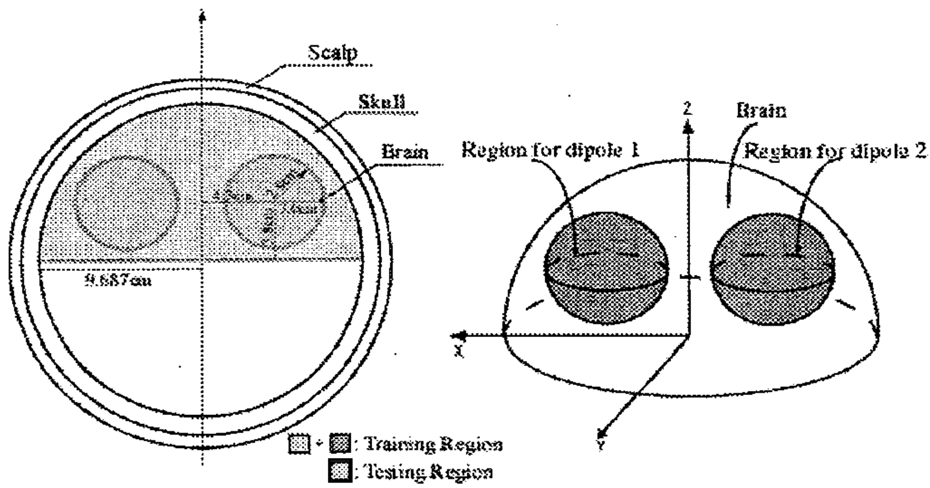
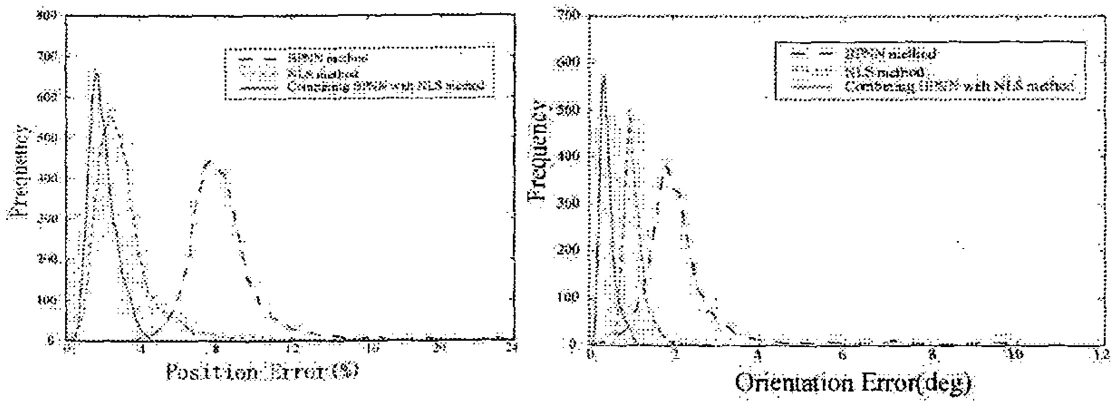


Fig.4 Restricted head model for some special clinical applications

To the second case mentioned above, the outputs of BPNN have been set as the initial value of iteration of the POWELL algorithm. In general case, after 4-7 times iteration it will get a convergent result. So this method is fast enough for real time

used here. To localize the dipole source in the brain with real head model will be focusing on the future works.



(a) (b)

Fig. 5 Error distributions obtained by three different methods

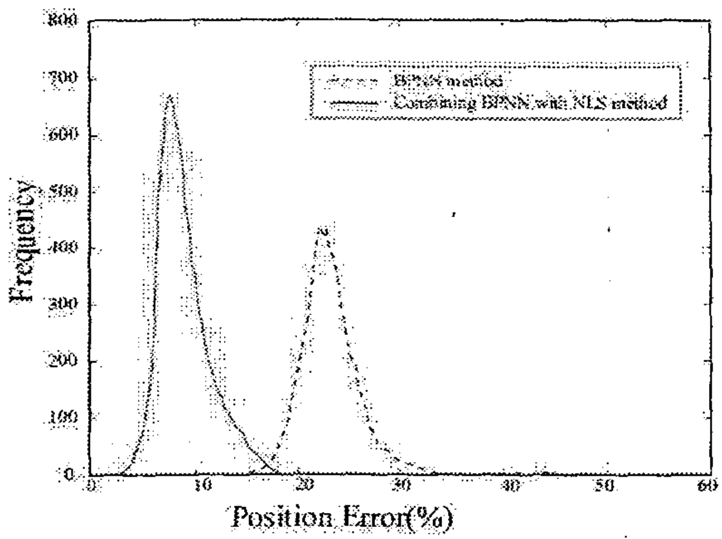


Fig. 5 Error distributions with 30% white noise from two methods

4 Conclusions

We here addressed the problem of estimating two biopotential sources in human brain, based on EEG signals measured on the scalp. In this paper, we proposed a method combining a neural network with a nonlinear least square method. It has been found from computer simulations that the method can estimate the parameters of the dipoles with the position error of less than 2.5% and direction error of 0.5 degree respectively in the condition of non-noise. Also the simulation showed us the average position error of less than 10% even in the condition of inserting 30% white noise. The accuracy is high enough for non-invasive and real-time localization.

Therefore, the proposed method may be very useful for clinical application.

Further experiment raw data will be fed into the system in order to prove the usefulness of the method .

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