

SINGLE DIPOLE SOURCE LOCALIZATION FROM CONVENTIONAL EEG USING BP NEURAL NETWORKS

Qinyu Zhang*, Motohiro Yuasa, Hirofumi Nagashino, Yohsuke Kinouchi
Dept. of Electr. and Electro. Eng., Univ. of Tokushima, Tokushima, Japan
*E-mail: zqy@ee.tokushima-u.ac.jp

Abstract—Brain source localization is an important inverse problem for brain diagnosis and functional analysis. The usefulness of BPNN(Back Propagation Neural Network) to solve this problem has been reported[1,2]. The purpose of this study is to examine the practical effectiveness of NN for single dipole source localization from EEG based on conventional 18 electrodes of a 10-20 system, and to investigate estimation accuracy in relation to EEG references, dipole positions and network training.

keyword—Brain source localization, EEG, Back-propagation, neural networks, Localization accuracy

I. INTRODUCTION

Source localization of EEG is a very useful and important part for studying brain function and for diagnostic purpose. We can regard the localization sources from EEG data as an inverse problem. With the increasing of the clinical application of EEG, it should be necessary to solve the inverse problem in real time, in spite of the complexity of brain and source models.

Some methods and minimization algorithms such as Simplex Method and the Marquardt algorithm to solve the inverse problem have been reported[3]. In general, in order to obtain a high localization accuracy from the EEG data of source parameters, long time computer times and huge memory should be requested. Therefore, a direct method to compute source parameters from a voltage set measured on the scalp is required. As one of this method, the usefulness of the neural network for EEG source localization in the case of single dipole source with 39 electrodes has been reported[1]. The number of electrodes should be reduced to use the neural network method practically.

The purpose of this study is to examine the practical effectiveness of NN (neural network) for single dipole source localization from EEG based on conventional 18 electrodes of a 10-20 system, and to investigate estimation

accuracy in relation to EEG references, dipole positions and network training.

In order to install the desired inverse function to the neural network, it should be trained by training patterns which may be obtained theoretically or experimentally, according to the complexity of the brain model and the field measurement system. Since trained neural networks have a calculation time of localization independent from the head model, the rapid localization ability makes it possible to employ the most complex head model as well as the simplest model as long as training data are obtained. Therefore, a simple head model is used here because of easy preparation of training data.

II. METHODS

To apply BPNN to EEG localization for single source, we have to determine a source model, a head model, an electrode configuration and a network structure.

A. Source Model, Head Model and Electrode Configuration

We used here a current dipole source model and three concentric shell model.

The head has been modeled in several ways depending on requirements and available computing power. Head models may be divided into the following three categories: (a) An uniform sphere model[4]; (b) A three concentric shell model[5]; (c) Complex models. Since the model (a) is very far from reality and the model (c) is very complex though realistic, three concentric shell model (b) is used in this study. Fig. 1 shows the structure of the head model and an electrode arrangement based on the 10-20 system.

B. Neural Networks Method

In this study, a BP neural network (using an error back propagation algorithm)[6] is used extensively for solving inverse problem. Usually, if an inverse problem has a unique solution, the network can solve the problem by

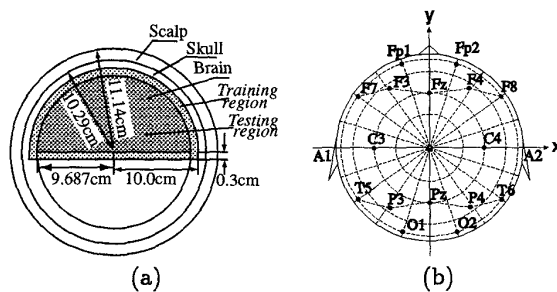


Fig. 1. Three concentric shell model (a) and 18 electrode positions in the 10-20 system (b)

only one forward calculation, without iterative convergence. Since the source localization problems for EEG are considered to have unique solutions, provided there are a finite number of sources, the neural network approach can be applied to the problem. The neural network method also results in a quick solution, regardless of the complexity of the model, as long as the training patterns are adequate.

Configuration of the neural network used is shown in Fig. 2. Fig. 3 shows the arrangement of neural networks for source localization. If an EEG pattern is fed into the network, the output will be an estimation of the position of the dipole, and the dipole moment. Here, the network consists of four layers (an input layer, 2 hidden layers, and an output layer). There are 16-18 neurons to receive the potentials from 16-18 electrodes in the input layer. There are 31 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 consists of only one neuron indicating one of the components of dipole position P , i.e., (x, y, z) or moment M , i.e., (M_x, M_y, M_z) . The six same structure networks are therefore used in parallel for position and moment estimations. That is, the network makes use of the independence of six source parameters. Neurons in the input layer have a linear input-output function, while other neurons have a sigmoid function (\tanh).

First of all we have to generate a set of data to train the networks. Dipole parameters and corresponding surface voltages give the output and input training data sets respectively. This phase is called the data generating phase. Training and testing patterns are generated by using an expression [1].

18 EEG potentials at the usual positions are calculated theoretically for a single current dipole put in a

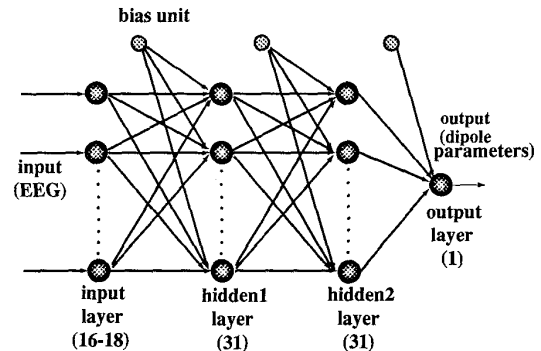


Fig. 2. Configuration of neural network

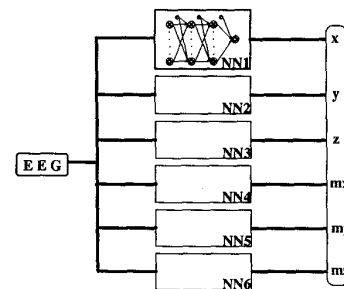


Fig. 3. Neural networks for source localization

hemisphere brain of three-concentric shell head model. A dipole is put randomly in the brain model. The training region is chosen to be larger than the testing region in order to obtain a high localization accuracy for the testing patterns. Here, 10,000 EEG-dipole parameters pairs calculated above are used for training the neural network by the error back propagation algorithm and tested by different 10,000 pairs to examine the localization accuracy. Learning parameters of neural network training are optimized and several error functions are used to control error distributions.

In order to investigate the effectiveness of the references, three types of reference electrodes are therefore chosen, i.e., (1) the mean of A_1 and A_2 potentials (16 or 18 channels for the neural network input); (2) A_1 or A_2 potential (17 channels) and (3) the average of all 18 potentials (18 channels). We also defined two kinds of regions to investigate the influence of the position of the source dipoles, i.e., (1) region A and region B as shown in Fig. 4. Here, region A means the area where the location of dipole opposite to the reference electrodes, and region B is in the reverse side. (2) center region and boundary

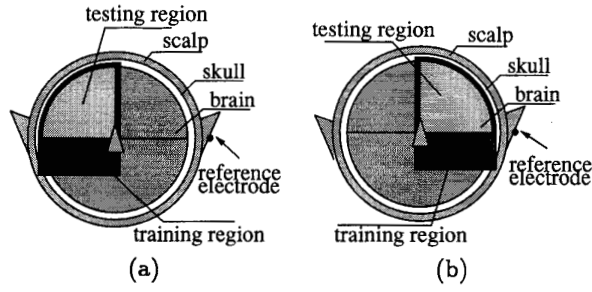


Fig. 4. Influence model for localization. (a)region A; (b)region B

region as shown in Fig. 5. In this case, center region means the area in deep brain where the source locates, and the boundary region is for opposition.

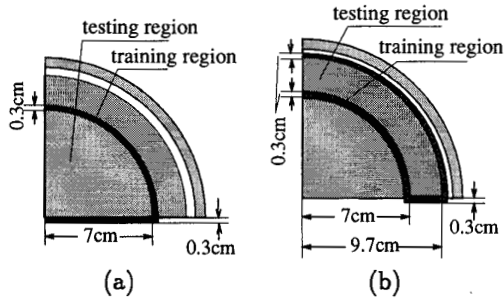


Fig. 5. Partial model for source localization. (a)center region; (b)boundary region

To train the network, the typical error back propagation algorithm is used [6]. The position error and direction error functions are defined as follows.

The position error[%]:

$$\epsilon_{pos} = \frac{1}{pat} \sum_{p=1}^{pat} \sqrt{(x_p - x'_p)^2 + (y_p - y'_p)^2 + (z_p - z'_p)^2} \quad (1)$$

where pat is the number of patterns, (x_p, y_p, z_p) and (x'_p, y'_p, z'_p) are the localized position by the neural networks and the actual position of p th dipole respectively.

The direction error[deg]:

$$\epsilon_{ang} = \frac{1}{pat} \sum_{p=1}^{pat} \cos^{-1} \left(\frac{(\vec{m}_p \cdot \vec{m}'_p)}{|\vec{m}_p| |\vec{m}'_p|} \right) \quad (2)$$

where m_p and m'_p are the localized and actual dipole moment vectors respectively of p th dipole.

III. RESULTS

Table I shows the localization accuracy for each reference. The average position errors of single dipole source localization are about 4% or less and the average direction errors of dipole moment are about 1 degree. It may give accuracy high enough for clinical use.

TABLE I
LOCALIZATION ACCURACY

Reference Electrodes	Position Error[%]		Direction Error[deg]	
	ave.error	max.error	ave.error	max.error
$\frac{A_1+A_2}{2}$ (16ch)	4.04	28.7	1.16	12.0
$\frac{A_1+A_2}{2}$ (18ch)	3.65	20.9	1.07	10.0
A_1 (17ch)	3.88	22.8	1.21	9.73
$\frac{F_{p1}+\dots+A_2}{18}$ (18ch)	3.27	24.8	0.97	8.76

Error distribution has been examined. The result is shown in Fig. 6 as a function of the distance between dipole position and the head center. It is found that the error increases with increasing the distance.

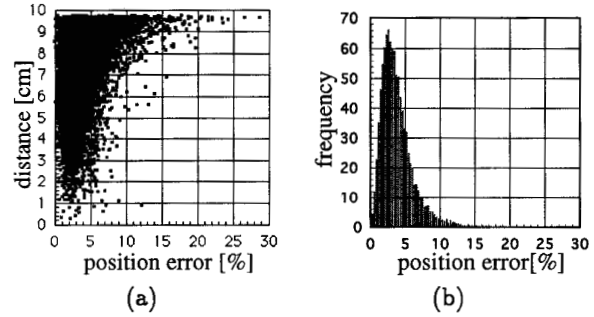


Fig. 6. Error distribution.(a)The relation between distance and position error.(b)The relation between frequency and position error

Table II and Table III show the localization accuracy for the influence of references and sources location.

TABLE II
LOCALIZATION ACCURACY FOR INFLUENCE MODEL

		region A	region B
		ave.error	3.5
position error	ave.error	3.2	3.5
	max.error	17.4	32.9
direction error	ave.error	1.0	1.2
	max.error	5.6	2.0

TABLE III
LOCALIZATION ACCURACY FOR PARTIAL MODEL

		center region	boundary region
position error	ave.error	2.4	5.6
[%]	max.error	11.6	48.9
direction error	ave.error	0.6	1.6
[deg]	max.error	4.2	9.8

IV. DISCUSSION

From table I, we can find, the magnitude of position errors somewhat depends on the references chosen and the average reference gives the smallest error. With the channels increasing, the errors became small. It may relate to the channel number connected with the neural networks input. We also investigated the influence of the source position in more detail in order to determine the cause of the errors. Table II shows the relation of the distance between the position of dipole and the position of the reference electrodes. The influence of position of reference electrodes is very large. A dipole near the reference electrodes may give a large position error because of activation of the electrodes. The neural network with a single reference (A_1 or A_2) is useful for this case. Position error for a half brain opposite to the reference decreases to 3.2% in average. Table III shows the relation of the distance between the source position and the brain boundary. If the dipole locates near the brain boundary, it also gives generally a large error. This may be caused by EEG spectra spreading in high space frequency. For example, the average position error for dipoles in deep brain area with 70% radius is as small as about 2.4%. Therefore, localization accuracy became considerably high except in the region near the boundary. In practical applications of this method, it may be necessary to decrease the variance of the error distribution, which can be achieved by controlling the learning rate. Trial clinical tests for an epileptic dipole source have shown the practical usefulness of the system.

V. CONCLUSIONS

The system combining neural network with 18 electrodes mostly used in clinics can estimate a dipole source by position errors of 3.3% to 4% in average that is applicable for clinical use. For neural network source localization, there are however some problems to be solved, such as noise tolerance evaluation, multi source localization and training data generated by FEM (Finite Element Method) for a realistic head model.

REFERENCES

- [1] R. Abeyratne et al., "Artificial Neural Networks for Source Localization in the Human Brain" *Brain Topography*, vol.4, no.1, pp.3-21, 1991
- [2] Y. Kinouchi et al., "Dipole Source Localization of MEG by BP Neural Net" *Brain Topography*, vol.8, no.3, pp.317-321, 1996
- [3] R.P. Gaumond et al., "Accuracy of Dipole Localization with a Spherical Homogeneous Model" *IEEE Tr. on Biomedical Engineering*, vol.BME-30, pp.29-33, 1983
- [4] M.R. Schneider et al., "A Multistage Process for Computing Virtual Dipole Sources of EEG discharges from Surface Information" *IEEE Tr. on Biomedical Engineering*, vol.BME-19, no.01, pp.1-12, 1972
- [5] S. Rush et al., "Current Distribution in the Brain from Surface Electrodes" *Anesthesia and Analgesia* 47, pp.717-723, 1968
- [6] D.E. Rumelhart and J.L. McClelland "Parallel Distributed Processing" *MIT Press, Cambridge*, 1996