Source Localization Techniques for Magnetoencephalography (MEG)

Kwang-Ok An, Chang-Hwan Im, Hyun-Kyo Jung, Yong-Ho Lee and Hyuk-Chan Kwon

Abstract - In this paper, various aspects in magnetoencephalography (MEG) source localization are studied. To minimize the errors in experimental data, an approximation technique using a polynomial function is proposed. The simulation shows that the proposed technique yields more accurate results. To improve the convergence characteristics in the optimization algorithm, a hybrid algorithm of evolution strategy and sensitivity analysis is applied to the neuromagnetic inverse problem. The effectiveness of the hybrid algorithm is verified by comparison with conventional algorithms. In addition, an artificial neural network (ANN) is applied to find an initial source location quickly and accurately. The simulation indicates that the proposed technique yields more accurate results effectively.
Keywords - artificial neural network (ANN), evolution strategy (ES), magnetoencephalography (MEG), neuromagnetic inverse problem, sensitivity analysis

1. Introduction

Yong-Ho Lee and Hyuk-Chan Kwon are with Korea Research Institute of Standards and Science, Daeieon, Korea.Recently, extensive research has investigated human brain activities using source localization with magnetoencephalo-graphy (MEG) and electroencephalography (EEG) [1, 2]. It is obvious that magnetic field (obtained by MEG) caused by current dipole sources is less affected by properties of head tissue than the electric potential (obtained by EEG). Another advantage of MEG compared to EEG is that the measured quantity is a field strength rather than a potential value; thus, the MEG is independent of the choice of a reference [3]. For these reasons, although the EEG has been widely used for current practical applications, further research is focused on the MEG rather than the EEG.

The MEG source localization is a kind of inverse problem with considerably high non-linearity. Usually, there are two different approaches to solve the "neuromagnetic" inverse problem. The first is to determine spatial parameters of a small number of dipoles by using optimization algorithms [4, 5]. The other is to determine the distribution of the currents in a brain [6, 7]. Because the former is thought to be more general and practical than the latter, the dipole source localization will be dealt with in this paper.

The most important subject in MEG source localization is to find current dipole sources more accurately with less effort. However, some problems remain to be solved. The first is that experimental data contain a lot of erroneous information due to noises from the external magnetic environment or the Superconducting Quantum Interference Device (SQUID) system itself. Such useless or erroneous information in the experimental data complicates estimation of the exact current dipole locations. To eliminate noise, preliminary handlings of the experimental data should be introduced in the signal processing stage [8, 9]. However, such algorithms usually fail to achieve their purpose ideally, leave distortion in the data, or even introduce new distortions [10]. The approach that will be introduced in this paper is rather different from the convention ones. The main objective is to compensate for the erroneous information rather than to remove the noisy signals.

The second subject lies in the use of optimization algorithms. In the MEG source localizing process, few measuring points are used for the reconstruction of the dipole sources. Since the given data contains very limited information, the inverse process becomes *ill-posed*. Therefore, obtaining exact solutions is difficult because the objective function is very complex and always has many local optima. To solve the problem, various optimization techniques have been adopted. Generally, there are two kinds of optimization algorithms: deterministic algorithms and stochastic algorithms. In case of the deterministic algorithms, although the convergence rate is usually very fast throughout the whole process, the deterministic algorithm is apt to converge to a local optimum for such a complex problem. Stochastic algorithms, such as genetic algorithm (GA) and simulated annealing (SA), which have been usually used for dipole source localization, take considerable time to converge to a global optimum [11]. Consequently, to obtain dipole source location accurately with less effort, some improvements in conventional algorithms are needed. In addition, a good estimation of the initial value should be implemented to reduce the computational cost.

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In this paper, an approximation technique using polynomial functions is proposed to reduce the errors in the experimental data. To improve the convergence characteristics in the optimization algorithms, a hybrid algorithm of evolution strategy (ES) and sensitivity analysis is applied. To estimate the initial dipole location and accelerate the convergence rate, an artificial neural network (ANN) is applied prior to the inverse procedure. The simulation results will prove that the proposed localization processes yield more accurate results effectively.

2. MEG Dipole Source Localization

2.1 MEG System

The human brain model is assumed to be a homogeneous conducting sphere. The assumption is usually acceptable except in some special cases. The magnetic field due to the current dipole is measured outside the model. Because the amplitude of the magnetic field is extremely small (about eight orders of magnitude smaller than the earth's magnetic field), this amplitude calls for not only very sensitive transducers, but also effective compensation and shielding against all sort of disturbances. Presently, such fields are mostly measured by low-noise SQUID systems. The SQUID system used for the experiment is shown in Fig. 1. Forty planar-type sensors that are composed of twenty x-directional sensors and twenty y-directional sensors can measure the spatial differences of tangential magnetic fields on the brain surface [12].

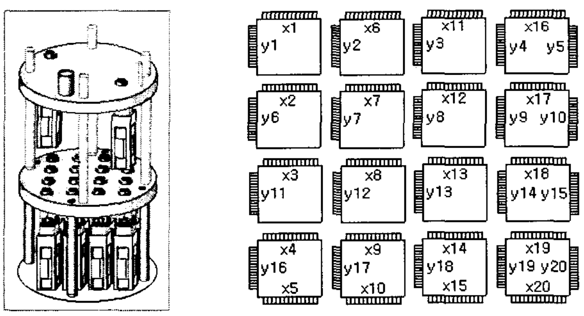


Fig. 1 Arrangement of forty SQUID sensors

2.2 Forward Solutions

As an approximation, the human head can be modeled by homogeneous conducting sphere. For such a model, the volume conductor effects can be expressed as an analytic formula. The magnetic field at a sensing position can be calculated by

$$\vec{B}(\vec{r}) = \frac{\mu_0}{4\pi}\sum_{i=1}^{N}\frac{F_i\vec{Q}_i \times \vec{r}_i' - \vec{Q}_i \times \vec{r}_i' \cdot \vec{r}\nabla F_i}{F_i^2} \tag{1}$$

where

$$\vec{a} = \vec{r} - \vec{r}_i'$$

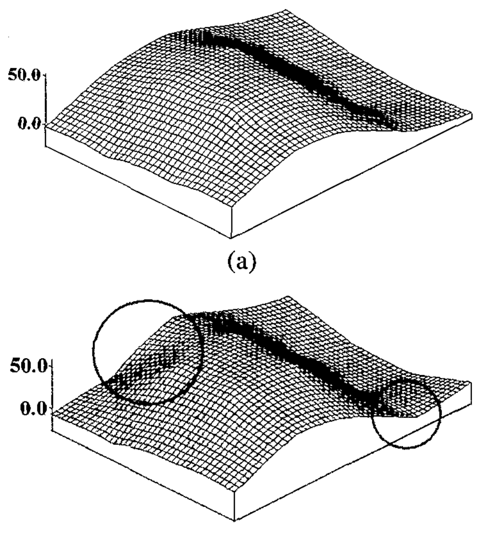
$$F_i = |\vec{a}_i|\left(|\vec{r}|\,|\vec{a}_i| + |\vec{r}|^2 - \vec{r}_i'\cdot\vec{r}\right)$$

$$\nabla F_i = \left(|\vec{r}|^{-1}|\vec{a}_i|^2 + |\vec{a}_i|^{-1}\vec{a}_i\cdot\vec{r} + 2\vec{a}_i + 2\vec{r}\right)\vec{r} - \left(\vec{a}_i + 2\vec{r} + |\vec{a}_i|^{-1}\vec{a}_i\cdot\vec{r}\right)\vec{r}_i'$$

and where $\vec{r}$ represents the position of sensors, $\vec{r}'$ the position of i-th dipole, N the number of the dipoles, and $\vec{Q}_i$ the i-th dipole moment [2].

2.3 Reduction of Errors in Experimental Data

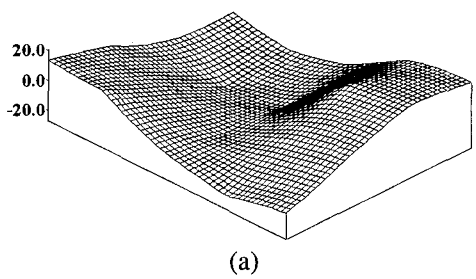
Generally, the magnetic source imaging (MSI) in neuromagnetic measurements includes a lot of errors. The errors may originate from the noise of the SQUID system itself or faults in handling the instruments during the experiment. The errors make the experimental data different from forward solutions even with the same dipole locations Fig. 2 and Fig. 3 show the difference between the forward solutions and the experimental data. We can see that the errors are somewhat severe at some regions marked by circles.



(a)

(b)

Fig. 2 Magnetic field distribution of x-directional sensors: (a) Forward solution and (b) Experimental data



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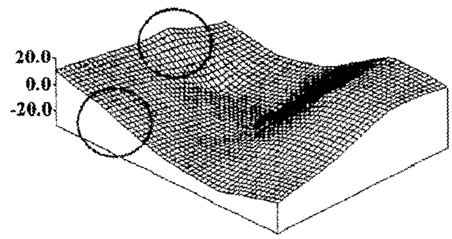


(b)

Fig. 3 Magnetic field distribution of y-directional sensors: (a) Forward solution and (b) Experimental data

In this paper, a polynomial function approximation is used to reduce the differences between the experimental field distributions and the forward solutions. To determine the order of the polynomials, the differences in coefficients of the polynomials between the experimental and the forward solutions are calculated for four types. Fig. 4 shows the results in case of second-, third-, fourth-, and fifth-order polynomials.

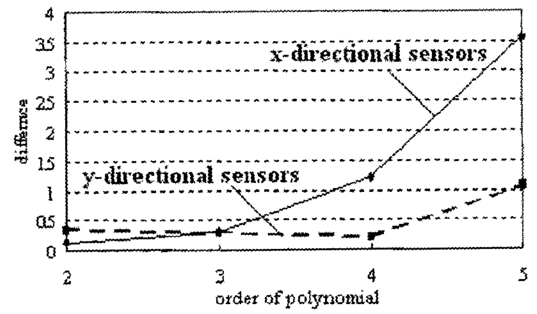


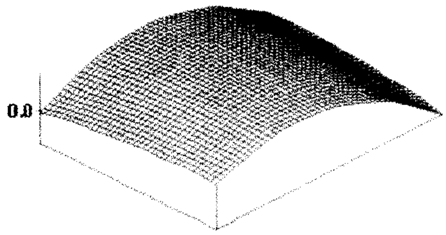
Fig. 4 The difference between the experimental field distribution and the forward solutions, according to the order of the polynomials

In case of second- and third-order polynomials, both x-directional sensors and y-directional sensors obtain very small differences. However, the second-order polynomial approximation represents the different distribution with forward solutions. Fig. 5 shows forward solution after second-order polynomial approximation.

Therefore, we used a third-order polynomial function as Eq. (2). It is found that the third-order polynomial function has the best characteristics for representing the magnetic field distribution induced by a 'single' dipole source. Numerous simulations verify that the polynomial function can represent the main feature of the distribution without losing the peak values or peak positions.

$$f(x,y)=a_0+a_1x+a_2y+a_3x^2+a_4xy+a_5y^2 +a_6x^3+a_7x^2y+a_8xy^2+a_9y^3 \quad (2)$$

ere the coefficients of the polynomials are obtained by ng the least square method. Then, the objective function he inverse problem can be represented by the difference the coefficients of the polynominal between the rimental and the calculated values.



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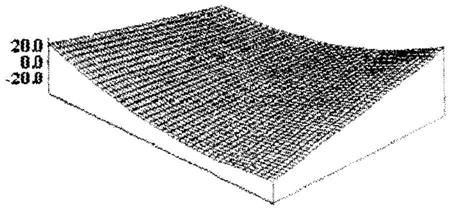
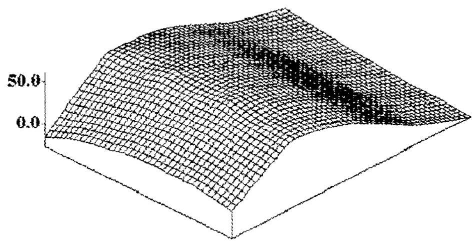


(b)

Fig. 5 Forward solutions after approximation: (a) x-directional sensors and (b) y-directional sensors

After using polynomial function approximation, the errors in the experimental data are reduced considerably. The comparison of the forward and the experimental data after the approximation is shown in Fig. 6 and Fig. 7.



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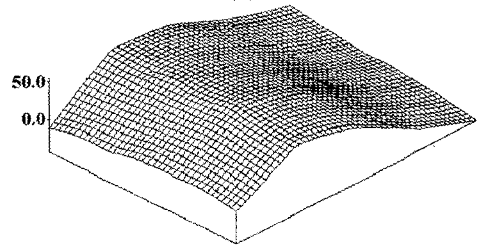

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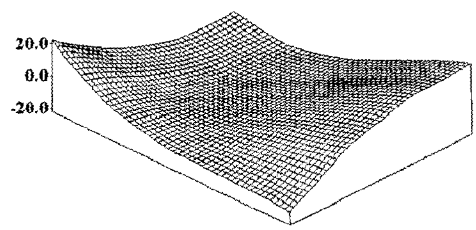
Fig. 6 Magnetic field distribution of x-directional sensors: (a) Forward solution after approximation and (b) Experimental data after approximation



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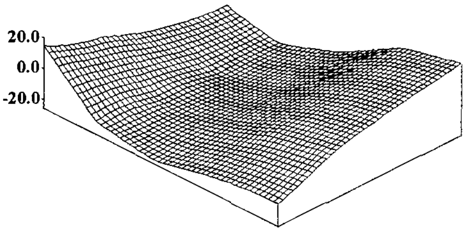

(b)

Fig. 7 Magnetic field distribution of y-directional sensors:
(a) Forward solution after approximation and
(b) Experimental data after approximation

2.4 Optimization Algorithm

1) Evolution Strategy

Among the several stochastic methods, the ES uses the principle of organic evolution as the rule to seek the optimal condition. The ES is widely used because it can find a global optimum and the structure of the algorithm is very simple [13 - 15].

To apply the ES, the objective function is defined as

$$OF = \frac{1}{2}\sum_{i=0}^{9}(a_{oi} - a_i)^2 \tag{3}$$

where i means the i-th coefficient, a_{oi} the coefficients of original experiment data, and a_i the coefficients of the calculated data.

2) Sensitivity Analysis

Sensitivity analysis is widely used because it can deal with a lot of design variables simultaneously and the convergence rate is very fast [16]. The objective function for the sensitivity analysis is the same as in Eq. (3).

3) Hybrid Method

When using the ES, the convergence rate is very fast in the beginning step. However, as the solution approaches an optimum, the rate becomes slower and slower. On the other hand, the convergence rate of sensitivity analysis is very fast throughout the whole process. However, if sensitivity analysis is used solely, it is apt to converge to a local optimum.

Therefore, the hybrid method of two algorithms is used for dipole source localization. The ES is used for finding an outline of the dipole location near an optimum, and sensitivity analysis is used for finding the exact location of the dipole.

2.5 Application of Artificial Neural Network

As stated previously, the hybrid algorithm is used in the inverse procedure. In applying the hybrid algorithm, a good estimation of the initial dipole location improves the computational cost of the inverse algorithm. To estimate the initial dipole location, an ANN is applied. In the case of a single dipole, the patterns of the magnetic field distribution are very simple. Therefore, the source location can be found using only peak positions and values.

The structure of the ANN is roughly shown in Fig. 8.

Input p_i represents the peak positions and values of magnetic flux density in the sensing plane. Output a_i represents the position vector (x, y, z) of an equivalent current dipole. The ANN consists of two layers: the first layer is composed of sixty neurons, and the second layer is composed of three neurons.

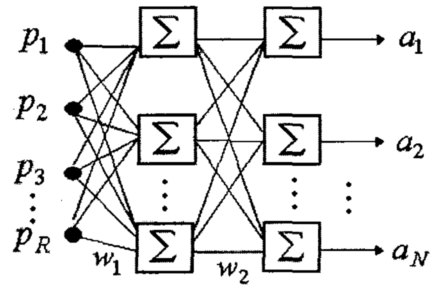

Fig. 8 The structure of the ANN

Prior to the application to real measurements, the ANN is trained to estimate parameters of the equivalent current dipole with a supervised training procedure. First, 550 cases with random dipole positions and directional vectors are simulated. Then, the peak positions and values of magnetic field distribution are found in the case of x- and y-directional sensors. Then, by using dipole parameters and peak values, the ANN is trained.

3. Simulation Results

To verify the effectiveness of the proposed methods, its performance is compared with that of conventional ones. The head model is assumed to be spherically symmetric conductor with an outer radius of 85 mm. The magnetic field data are measured by forty SQUID planar gradiometers, which are shown in Fig. 1.

3.1 Error Reduction of Experimental Data

Table I shows the comparison of accuracy of the before- and after-approximation process. Two cases use the ES algorithm when same terminal condition is applied; the value of the objective function is 0.99. The units of x,y,z, and r are mm, and those of θ and φ are rad. The values in parentheses mean the differences between exact and calculated data. The table shows that the result after polynomial function approximation is more accurate than that before the approximation, especially in the value of z.

Table 1 Comparison of Results between Before and fter Approximation

variables	before approximation	after approximation
x [mm]	13.3 (1.0)	13.2 (0.9)
y [mm]	49.9 (0.9)	48.2 (0.8)
z [mm]	34.7 (4.5)	40.1 (0.9)
r [mm]	1.01 (0.02)	0.89 (0.1)
θ [rad]	0.03 (0.13)	0.87 (0.71)
φ [rad]	-0.42 (0.13)	0.37 (0.66)

3.2 Artificial Neural Network

Table II shows the capability of the ANN to estimate initial source location. By using just peak value and peak positions of magnetic field distribution in a sensing plane, the initial source location can be estimated accurately.

Table 2 Comparison of Exact Position and Estimated Position

	x	y	z
Exact position	12.3	49.0	39.2
Estimated position	12.7	55.3	38.0

3.3 Optimization Algorithm

Table 3 compares the four optimization algorithms in terms of the total iteration number and accuracy of inverse results. The results verify that the hybrid algorithm is more effective than the ES or sensitivity analysis and the convergence rate can be accelerated by estimating the initial location using an ANN.

Table 3 Comparison of Four Optimization Algorithms

	x	y	z	r	θ	φ	# of iteration
Exact	12.3	49.0	39.2	0.99	0.16	-0.3	
ES	13.2	48.2	40.1	0.89	0.87	0.37	1830
Sen.	-8.8	49.7	17.2	0.93	0.56	0.64	464
Hybrid	12.3	48.6	40.2	0.87	0.85	0.13	1017
ANN & hybrid	12.2	48.9	38.5	0.92	0.09	-0.4	406

4. Conclusions

This paper introduces techniques for magnetoencephalo -graphy source localization. To reduce errors in experimental data, a polynomial function approximation was applied to the pre-process. The ES, sensitivity analysis, and the hybrid algorithm for MEG source localization were compared. In addition, an ANN is applied to find the reliable source location quickly. Simulation results verify the efficiency and validity of the proposed processes.

Acknowledgment

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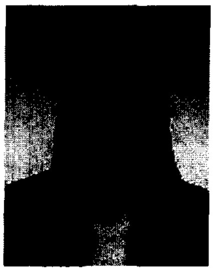

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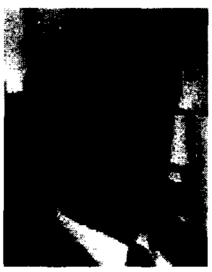

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