Application of a Hybrid Approach to Magnetoencephalography Dipole Source Localization

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Abstract: MEG is a useful method to know brain activities. The process of determining the neural sources from the measured MEG is known as the inverse problem. To improve source localization accuracy and reliability, we use a hybrid algorithm during the scanning procedure, i.e., quasi-Newton (QN) method for a high-speed coarse scanning over a large area of the head, and Levenberg-Marquardt (LM) method for a fine scanning near the source area. Experimental data shows this proposed algorithm be more efficient both in computation time and sensitivity to the iterative initial value.

Keywords: MEG, hybrid, optimization, source localization

1. Introduction

Measurements of the magnetoencephalography (MEG) provide unique insights into the dynamic behavior of the human brain as they are able to follow changes in neural activity on a millisecond time-scale [1]. The core of MEG research is its inverse problem, that is, given a suitable source and head model, we have to solve a nonlinear optimization problem of computing the location and moment parameters of the set of dipoles whose field best matches the measured magnetic data outside the head in a least squares sense [2].

As shown in Fig.1, various optimization techniques have been adopted to solve this dipole source localization. Here, A hybrid algorithm to vary the used optimization method during the source scanning procedure is introduced. We use quasi-Newton (QN) method for a high-speed coarse scanning over a large area of the head, and Levenberg-Marquardt (LM) method for a fine scanning near the source area. By several computer simulations, this synthetic approach proved to be more efficient both in terms of computation time and sensitivity to the iterative initial value.

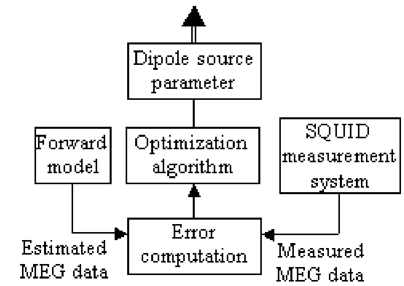

Fig.1 Diagram of nonlinear optimization methods to estimate the dipole parameter

2. Method

β represents dipole parameter vector, and $r(\beta)$ is residual error function between the measured and computed data.

LM method is proposed by Levenberg(1944) and Marquardt(1963). And Cuffin(1985) introduced this method into MEG source localization. Considering the confidence field model,

$$\lambda_k = \frac{E(\beta_{k+1}) - E(\beta_k)}{(J(\beta_k)^T e(\beta_k))^T d_k + \frac{1}{2}(d_k)^T (J(\beta_K)^T J(\beta_k)) d_k} \quad (1)$$

If $\lambda_k < 1/4$, then set $\mu_{k+1} = 4\mu_k$; else if $\lambda_k > 3/4$, then $\mu_{k+1} = \mu_k / 2$; else $\mu_{k+1} = \mu_k$. So we have

$$\beta_{k+1} = \beta_k - (J(\beta_k)^T J(\beta_k) + \mu I))^{-1} J(\beta_k)^T e(\beta_k) \quad (2)$$

set $k = k+1$, do iteration, end until $\left\| J(\beta)^T e(\beta) \right\| \le \xi$.

In addition, we adopt Q-N algorithm proposed by Dennis et al.(1981), B_k should satisfy quasi-Newton condition,

$$B_{k+1}(\beta_{k+1}-\beta_k)=(J(\beta_{K+1})-J(\beta_k))^T e(\beta_{k=1}) \quad (3)$$

Moreover, B_k should satisfy the correcting quasi-Newton condition

$$B_{k+1}=B_k+\frac{(y_k-B_k s_k)v_k^T+v_k(y_k-B_k s_k)^T}{s_k^T v_k} - \frac{s_k^T(y_k-B_k s_k)}{(s_k^T v_k)^2} v^k v_k^T \quad (4)$$

Where

$$y_k=(J(\beta_{K+1})-J(\beta_k))^T e(\beta_{k=1})$$
$$v_k=J(\beta_{K+1})^T e(\beta_{k+1})-J(\beta_k))^T e(\beta_k)$$
$$s_k=\beta_{k+1}-\beta_k$$

So we have

$$\beta_{k+1}=\beta_k-(J(\beta_k)^T J(\beta_k)+B_k+\mu_k I))^{-1} J(\beta_k)^T e(\beta_k) \quad (5)$$

set $k=k+1$, do iteration, stop until $\left\|J(\beta)^T e(\beta)\right\| \le \xi$.

Actually, both LM and QN adopt the confidence field model, so global convergence is guaranteed. During every steps, the former algorithm is

$$\begin{aligned} &\min\{e(\beta_k)+(\beta-\beta_k)J(\beta_k)\} \\ &s.t. \quad \|\beta - \beta_{\mathrm{k}}\|_2 \le \xi_k \end{aligned} \quad (6)$$

and the latter is

$$\min\left\{\begin{aligned}&\frac{1}{2}e(\beta_k)^T e(\beta_k)+(\beta-\beta_k)^T J(\beta_k)^T e(\beta_k)+ \\ &\frac{1}{2}(\beta-\beta_k)^T (J(\beta_k)^T J(\beta_k)+B_k)(\beta-\beta_k\end{aligned}\right\} \quad (7)$$
$$s.t. \quad \|\beta - \beta_{\mathrm{k}}\|_2 \le \xi_k$$

In this paper, the hybrid algorithm presented is combine LM with QN method. According to the result of the every step of iteration, we select the former or the latter method to continue searching. While *r*(β) is small (the smaller difference between the measured magnetic data and computed data means the selected β near β^{true}), we adopt LM in order to get a rapid convergent speed. Otherwise, while *r*(β) is large(means β far away β^{true}), QN is needed, rapidly toward the true source parameters and save the computation time. Until all of the increments become smaller than a predetermined minimum value, we can therefore obtain the last solution. In order to combining the two algorithm, the decision criterion is difined as

$$E(\beta_k)-E(\beta_{k+1}) \ge \tau E(\beta_k), \quad \tau \in (0,1) \quad (8)$$

3. Results

Magnetic induction intensity can be computed by the following formula:

$$b_{mr}(R_m,\Theta_m,\Phi_m)=\frac{\mu}{4\pi}\sum_k \frac{A_{km}p_{k\theta}+B_{km}p_{k\phi}}{C_{km}^{\;3/2}} \quad (9)$$

Where
$$\begin{aligned}
A_{km} &= \rho_k(\cos\varphi_k \sin\Theta_m \sin\Phi_m - \sin\varphi_k \sin\Theta_m \cos\Phi_m) \\
B_{km} &= \rho_k[\sin\theta_k \cos\Theta_m - \cos\theta_k \sin\Theta_m \\
&\quad (\cos\varphi_k \cos\Phi_m + \sin\varphi_k \sin\Phi_m)] \\
C_{km} &= (R_m \sin\Theta_m \cos\Phi_m - r_k \sin\theta_k \cos\varphi_k)^2 + \\
&\quad (R_m \sin\Theta_m \cos\Phi_m - r_k \sin\theta_k \sin\varphi_k)^2 + \\
&\quad (R_m \cos\Theta_m - r_k \cos\theta_k)^2 \\
\mu &= \mu_0 = 4\pi 10^{-7}\,\mathrm{Hm}^{-1}
\end{aligned}$$

(R_m,Θ_m,Φ_m) and $(\rho_k,\theta_k,\varphi_k)$ are location parameters of *m-th* sensor outside the head and *k-th* dipole p_k respectively, $p_{k\theta}$, $p_{k\phi}$ represents two tangential moment component of *k-th* p_k.. And radius of spherical head is 10cm, R_m is 11cm.

We simulate the 37-channels measurement system produced by Bti Inc., so sensors are placed in the following mode: one is $\Theta=0$; and 6, 12, 18 measured points in three circles, i.e., $\Theta=\pi/8, \Phi=k_1\pi/3; \Theta=\pi/4, \Phi=k_2\pi/6$; $\Theta=3\pi/8, \Phi=k_3\pi/9$ (k_1=0,…,5; k_1=0,…,11; k_1=0,…,17).

Set SNR=$\sqrt{\sum_{i=1}^{M} b_i^2}/\sigma$. Meanwhile define a performance index parameter *W*, which representing ratio between number of solution and initial valve which random produced in solution space. Simulated dipole parameters is list in Table1, and the estimated results in Table 2. By comparison, this hybrid approach shows better performance, e.g., more efficient both in terms of computation time and sensitivity to the iterative initial value.

Table1. Simulated dipole parameters

dipole	ρ (cm)	θ (deg)	φ (deg)	p_θ (nAm)	p_φ (nAm)
A	7.37	43.00	72.00	4.5	13.3
B	7.20	53.00	59.00	3.7	10.0
C	7.20	46.00	60.00	10.0	8.5

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Table2. Estimated results

	SNR			$\rho\pm\sigma_\rho$	$\theta\pm\sigma_\rho$	$\varphi\pm\sigma_\rho$	$p_\theta\pm\sigma_\rho$	$p_\varphi\pm\sigma_\rho$	W
Test1	noiseless	LM	A	7.37	43.00	72.00	4.5	13.3	381/600
		LM-QN	A	7.37	43.00	72.00	4.5	13.3	479/600
Test2	180	LM	B	7.14±0.09	53.69±0.43	59.06±0.61	3.72±0.78	9.96±0.40	39/600
			C	7.22±0.08	46.23±0.33	60.17±0.31	9.78±0.28	8.44±0.39	
		LM-QN	B	7.23±0.08	52.91±0.55	59.10±0.19	3.71±0.75	10.12±0.26	51/600
			C	7.20±0.04	46.30±0.19	61.77±0.40	9.91±0.25	8.54±0.11	