Adaptive brain imaging: a simulation study

Conference or Workshop Item

Adaptive Brain Imaging: a simulation study

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Abstract. Most approaches to the Magnetoencephalographic (MEG) inverse problem (calculating the most likely sources underlying a given magnetic field measurement) start with a conductor model of the head in order to calculate the magnetic fields arising from a given source (known as the forward problem). The adaptive brain imaging approach involves simultaneously adapting the conductor model of the head whilst solving the inverse problem. The adapted conductor model can then be used to obtain a more accurate solution of the inverse problem.

Keywords: MEG, forward problem, inverse problem, lead field

1. Introduction

In this paper we will describe a new approach to the Magnetoencephalographic (MEG) inverse problem (i.e. calculating a likely source for a given magnetic field) that we call adaptive brain imaging. The approach is to adapt the conductor model used in the MEG forward problem (i.e. calculating the magnetic field arising from a given source). This paper is the first of a series of papers on this topic: here we briefly describe the approach and illustrate it with a simple simulation study.

For the simulation study we used the experimental geometry depicted in Fig. 1(A). The detector system geometry is that of the NeuroMag VectorView MEG instrument: there are 102 measurement sites with a magnetometer and two planar gradiometers at each site (a total of 306 channels of information). Also shown in Fig. 1(A) is a conducting sphere centred at the origin, which is used later to generate simulated data.

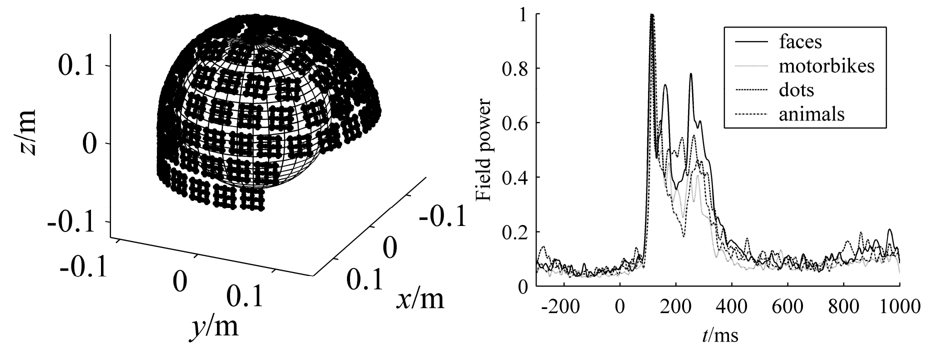

Fig. 1. (A) VectorView detector system with spherical conductor model. (B) Global field power (GFP) for MEG data from [3] showing the face specific response at about 140ms together with a stronger, more dipolar peak at about 100ms. The first peak could be used to adapt the lead fields for the analysis of the second peak.

The adaptive brain imaging idea arose when investigating the MEG data shown in Fig.1(B). The feature of interest in this data is the peak in the global field power at around 140ms, which appears when the subject is presented with an image of human face, as opposed to other images [3]. Earlier in the dataset there is a more well known (and stronger) response at around 100ms. The question arises as to whether the presence of the well known response can be used to improve the accuracy of the imaging of feature of interest. The next section outlines our approach. Section 3 presents the simplest test of the method, using the simplest conductor model. These results are discussed in Section 4.

2. Methods

The main steps of the Adaptive Brain Imaging approach are:

1. Select a time interval with a well defined underlying source (here assumed to be a rotating equivalent current dipole (ECD)) to obtain a data matrix *m* of size (#channels)×(#timeslices).
2. Parameterize the lead fields by θ so that a dipole at position *r* with moment *q* gives a signal $L^{\theta}(r)\bullet q$. For the illustrations in Section 3 we use the Sarvas sphere model [1] with the parameter θ being the sphere centre (X_c, Y_c, Z_c).
3. Find $\hat{r}$, $\hat{\theta}$ that minimize the cost function
   $C(r, \theta) = \| L^{\theta}(r)\bullet q - m\|_F^2$,
   where *q* is the 3×(#timeslices) matrix of optimum dipole moments (obtained by solving a linear problem) and $\| \|_F$ is the Frobenious matrix norm. This is the step that involves simultaneously estimating source positions and conductor model parameters.
   Several alternative cost functions have been investigated, for example using other matrix norms. A promising alternative cost function which measures the non-gaussianity of the residual
   $C(r,\theta) = \mathrm{kurt}(L^{\theta}(r)\bullet q - m)$,
   where $\mathrm{kurt}(x)= E(x^4)-3E(x^2)^2$ is the kurtosis (we use this definition of kurtosis, rather then the more standard definition $E(x^4)/E(x^2)^2-3$, because we want linearity: for our definition kurt(x+y)=kurt(x)+kurt(y)). Initial studies indicate that the cost function based on the kurtosis of the residual is less robust, so it is not used further in this paper.
4. Use the adapted lead fields $L^{\hat{\theta}}(r)$ for further analysis. Of course, the further analysis does not need to use the ECD source model: it can be any method designed to image unknown sources, such as linear source methods (minimum norm estimation (MNE), magnetic field tomography (MFT) or low resolution tomography (LORETA)) or beamforming methods

3. Results

As mentioned above, we use the geometry shown in Fig. 1(A) to generate test data from a single dipole located at $[0, 0.025, 0.08]^T$ rotating through 180º in 10ms sampled at 1kHz. To this pure signal we add uncorrelated gaussian noise of equal power to the signal (so the signal to noise ration is approximately 2). The question arises as to whether the true conducting sphere centre can be recovered from this short sample of data. Fig 2 shows that the cost function described above can indeed recover the true sphere centre — the cost function has a single minimum at the correct position (i.e. the origin). The single global minimum of the cost function can be found with many optimisation algorithms, for example the Nelder–Mead simplex algorithm locates the true sphere centre to millimetre accuracy.

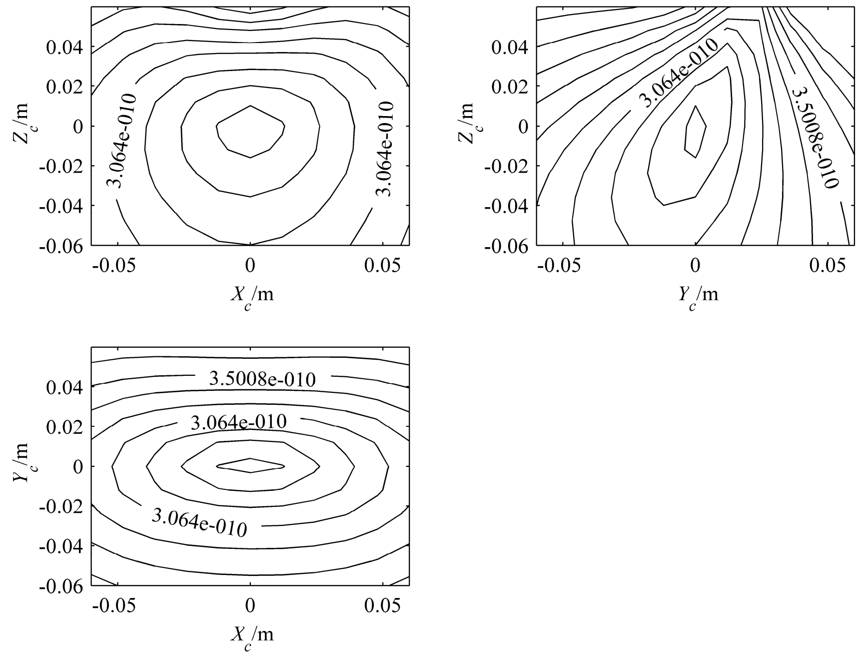

Fig. 2. Plots showing the global minimum of the cost function $C([X, Y, Z]^T,[X_c, Y_c, Z_c]^T)$. The contour maps shown correspond to the three location parameters of the sphere centre — it is well known that the dipole position parameters have a similar global minimum at the correct position. It is worth noting that the minimum in the sphere centre parameter is more shallow than the dipole location parameters.

Fig. 3 shows the effect of the assumptions of the approach not being satisfied, i.e. the data does is not generated from a source of the assumed form. In this simple example we assume that the ECD model applies, so consider adding a second dipolar source located at $[0.02, 0.025, 0.08]^T$ (i.e. close to the original dipole) with fixed dipole moment (50% of strength of first dipole). Fig 3 shows that the cost function still has a single global minimum (i.e. the nice properties of the cost function are preserved), but the minimum has moved slightly (i.e. the erroneous assumption (the ECD model) has manifested itself in a mislocation error of approximately 1cm).

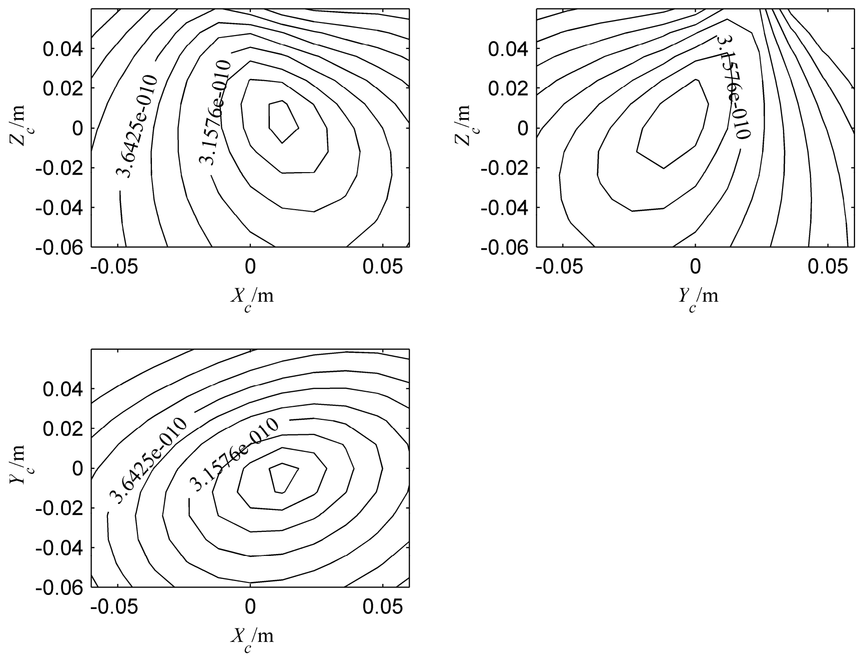

Fig. 3. Plots of the variation of the cost function variation of the sphere parameters for the two dipole test data.

4. Conclusion

The outlined approach can be used to increase the accuracy of any source localization algorithm. Fig. 1(B) already has a well characterised source for refining the lead fields. In other experiments we suggest that in between presentations of the main stimulus there is a training stimulus (a stimulus known to evoke a dipolar response) that is used to adapt the lead fields.

One application of this adapted single sphere model is fetal MEG, where one source of error is the (mis)location of the head of the foetus. Another application could be MEG screening applications, where the MRI of the subject is not available.

In future work we intend to investigate displacing a BEM model by an affine transformation to correct for co-registration errors and adding parametric correction terms to an existing lead field model (Nolte's method [2] is ideally suited for this).

References

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