Frequency-difference MIT imaging of cerebral haemorrhage with a hemispherical coil array: numerical modelling

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Abstract

The feasibility of detecting a cerebral haemorrhage with a hemispherical MIT coil array consisting of 56 exciter/sensor coils of 10 mm radius and operating at 1 and 10 MHz, was investigated. A finite difference method combined with an anatomically-realistic head model comprising 12 tissue types, was used to simulate the strokes. Frequency-difference images were reconstructed from the modelled data with different levels of the added phase noise and two types of a-priori boundary errors: a displacement of the head and a size scaling error. The results revealed that a noise level of 3 m° (standard deviation) was adequate for obtaining good visualisation of a peripheral stroke (volume \( \approx \) 49 ml). The simulations further showed that the displacement error had to be within 3-4 mm and the scaling error within 3-4% so as not to cause unacceptably large artefacts on the images.

Keywords: magnetic induction tomography, haemorrhagic cerebral stroke

1. Introduction

The feasibility of using magnetic induction tomography (MIT) for detecting lesions in the brain has been the subject of a number of modelling studies. Merwa and Scharfetter (2007) simulated MIT measurements at a frequency of 100 kHz with a 4-tissue finite-element head model containing a sphere of raised conductivity simulating oedema. Images of the lesion were reconstructed and with a SNR of 40 dB, a lesion 40 mm in diameter could be visualised. Again with a 4-tissue head model, but of simple geometry, Vauhkonen et al (2008) simulated different regions of raised conductivity representing haemorrhagic strokes and reconstructed images.

By adapting the realistic 12-tissue model of the head model developed by Horesh et al (2005) for EIT, Zolgharni et al (2009a) simulated MIT measurements and reconstructed images for different levels of phase noise in the measurements. A noise level of 1 m° (millidegree) was shown to be adequate for visualising a haemorrhage 7.7 cm³ in volume, centrally located in the brain. In all these studies, the images were in effect, time-difference images in which the changes in MIT signals from before to after the appearance of the lesion were used to reconstruct the images. Time-difference imaging could eventually be of clinical use for monitoring patients at risk or for monitoring the progression of a lesion. However, for making an initial diagnosis, time-difference imaging will not be suitable since no before-lesion reference data set will normally be available.

Frequency-differential methods have begun to be explored in order to overcome this limitation and depend on the ability to distinguish the “frequency signature” of the lesion from that of the surrounding tissues, all of which will have frequency-dependent electrical conductivities. Brunner et al (2006) imaged vegetable material immersed in saline solution and reconstructed its conductivity spectrum (100-700 kHz) from both simulated and measured multi-frequency MIT data. The frequency-dependent conductivity of the vegetable was visualised against the zero background of the surrounding saline solution, the conductivity of which was invariable with frequency.
With the aim of detecting cerebral haemorrhage, Zolgharni et al (2008) modelled frequency-difference MIT imaging with an annular array of 16 coils, again using the 12-tissue head model. Frequencies of 1 and 10 MHz were chosen so as to encompass the dielectric dispersion of blood centred on about 7 MHz (Gabriel et al 1996). The reconstructed MIT images showed the stroke lesion against a background of changes in all the other tissues and the conductivity changes in the neck dominated the image. In a subsequent study, Zolgharni et al (2009c) modelled a hemispherical coil array designed to increase the sensitivity to the brain and to reduce the sensitivity to the neck; frequency-difference MIT images of a large peripheral haemorrhage were reconstructed.

Eichardt et al (2009) have recently confirmed the better sensitivity distribution of the hemispherical arrangement. Construction of a 15-channel hemispherical helmet-shaped MIT device for brain imaging was recently reported by Zheng et al (2009). A bowl filled with saline solution was used to represent the brain and agar blocks of higher conductivity represented the haemorrhage. The inverse problem was not solved but 2D pseudo-images of the conductivity distribution at different frequencies (40-120 kHz) were generated using an interpolation algorithm.

In this paper we report an extension of the studies of Zolgharni et al (2008, 2009c) in which the 12-tissue head model is used firstly with the annular and then with the hemispherical coil arrangement. Simulations of frequency-difference MIT imaging of haemorrhagic strokes were performed for different levels of random phase noise and for two types of systematic errors that are likely to arise in a practical imaging system.

2. Methods and materials

2.1 Simulated MIT systems

2.1.1 Annular array

The first coil array modelled was similar to the Cardiff MK1 MIT system consisting of 16 pairs of exciter/sensor coils arranged in two concentric rings, but here the rings were smaller, having radii of 100 and 110 mm for exciters and sensors respectively (Watson et al 2008). The radii of the coils themselves were also smaller, at 10 mm. The array was positioned at 3 different heights with respect to the simulated head as shown in figure 1a. This provided a total of 768 (3×16×16) independent measurements. The middle plane passed through the centre of a simulated large peripheral haemorrhagic stroke. The coil array was similar to that used by Zolgharni et al (2008), but here the discretisation of the domain and the spacing of the 3 planes are different in order to match more closely the vertical extent of the helmet configuration described in the next section. This configuration will be referred to as “MK1”.

2.1.2 Helmet array

The helmet MIT array consisted of 28 exciter and 28 sensor coils, of 10 mm radius, positioned on a hemisphere (figures 1b-c). Two different helmet radii, 100 and 120 mm were considered and will be referred to as “H100” and “H120” respectively. The closest distance between a coil and the surface of the head was 5 mm for H100. This particular arrangement of the coils was adopted as it conformed better to the region of interest for imaging, the brain. This array provided 784 independent measurements.
Figure 1. The two MIT arrays simulated. (a) MK1 annular array. The 3 levels of the array are indicated as $Z_1 = 0$, $Z_2 = 38$ mm, and $Z_3 = 70$ mm against the side view of the head. At each level, two pairs of coils are shown: red-outer = exciter, black-inner = sensor. (b) Side view of the hemispheres H100 and H120 in position over the head. (c) Positions of the coils on the hemisphere, H100 (magnified in relation to a and b). 4 dots have been added to each exciter (red) coil to allow them to be distinguished on a grey-scale reproduction. The angles of elevation of the centres of the coils in each ring are indicated with respect to the lowest ring. The origin of the coordinate system is defined as the centre of the helmet.

2.2. The forward problem

The forward problem for MIT requires the solution of Maxwell’s equations for a set of given boundary conditions and prescribed materials. In previous work (Zolgharni et al 2009b) we employed an edge finite element (FE) discretisation to approximate the forward problem. However, in this study, an alternative approach, with a smaller computational footprint, was adopted.

2.2.1 Finite difference discretisation

The simplified model for the forward MIT problem consists of the following boundary value problem in a conducting domain $\Omega$ with boundary $\partial \Omega$ (Zolgharni 2010): Determine the scalar potential $\phi$ such that

$$\nabla \cdot \left((\sigma + i\omega \varepsilon) \nabla \phi\right) = -i\omega\nabla(\sigma + i\omega \varepsilon) \cdot \mathbf{A}(r, J_0) \text{ in } \Omega \quad (1a)$$

$$\frac{\partial \phi}{\partial n} = -i\omega \mathbf{A}(r, J_0) \cdot \mathbf{n} \text{ in } \partial \Omega \quad (1b)$$

where $\sigma$ is conductivity, $\varepsilon$ is permittivity, $\omega$ is angular frequency, $\mathbf{n}$ is the unit outward normal to $\partial \Omega$, $J_0$ is the current density in the exciter coils, $\mathbf{A}$ is an approximation to the magnetic vector potential $\mathbf{A}$, and $\mu^2 = -1$. Under the assumption of quasi-static fields with negligible wave propagation effects, and following Gencer and Tek (1999) and Morris et al (2001), $\mathbf{A}$ can be computed from:

$$\mathbf{A}(r, J) = \frac{\mu_0}{4\pi} \int \frac{J}{|r|} dv \quad (2)$$

where $J$ is some current density, and $\mu_0$ is the permeability of free space. The finite difference (FD) discretisation of (1) consists of a regular cubic grid, in which $\sigma$ is assumed to be constant in each voxel, and
a central difference approximation for the term \( \nabla \cdot (\sigma \nabla \phi) \). The induced voltage, \( V \), was calculated as the line integral of the tangential components of the vector potential \( A \) around the sensing coil:

\[
V(\mathbf{A}) = -i\omega \mathbf{A} \cdot \mathbf{d} \tag{3}
\]

where \( \mathbf{d} \) is element of the coil. To compute the primary signal, \( V(\mathbf{A}(\mathbf{r},\mathbf{J}_0)) \approx V(\mathbf{\hat{A}}(\mathbf{r},\mathbf{J}_0)) \) was used. To obtain the secondary signal, \( V(\mathbf{A}(\mathbf{J}_e,\mathbf{r})) \approx V(\mathbf{\hat{A}}(\mathbf{J}_e,\mathbf{r})) \) is employed, where \( \mathbf{J}_e = \sigma \mathbf{E} \approx -i\omega (\omega \mathbf{\hat{A}}(\mathbf{r},\mathbf{J}_0) + \nabla \phi) \) is the eddy current. Further details can be found in Morris et al (2001). Clearly by adopting this simplified model of the forward model, a number of assumptions are made. Firstly, \( \nabla \cdot \mathbf{A} = 0 \) is assumed but not enforced. Secondly, wave propagation effects are ignored. Thirdly, by replacing \( \mathbf{A} \) by \( \mathbf{\hat{A}} \) in equation (1), we assume that the contribution to \( \mathbf{A} \) relating to the conductive effects of the object are ignored. The applicability of this model to MIT is of on-going debate. However, comparisons with experimental data and finite-element simulations suggest that for a small range of parameters and geometries, reasonable results can be obtained (Zolgharni 2010).

The anatomically-realistic, multi-layer, tetrahedral mesh developed for electrical impedance tomography by Horesh et al (2005) was used as a basis for the geometry of the head model in this study. The tetrahedral mesh was mapped onto a 2 mm cubic mesh for use in the FD solver; a total of 474,897 cubic elements were used to represent the head (figure 2a). (The model does not require the space outside the head to be discretised.) Three intra-cerebral haemorrhagic strokes with different volumes and positions were introduced within the right hemisphere of the brain, replacing the normal tissue: a large peripheral stroke (LP, volume 49.4 ml), a small peripheral stroke (SP, 8.2 ml) and a small deep stroke (SD, 7.7 ml) (figures 2b-d). The volumes of the lesions ranged from 0.8 to 4.8 % of the total volume of the brain.

![Figure 2.](image)

(a) The head model (2.5 mm cubic elements) with two cuts illustrating the internal structure, including the LP stroke in the right hemisphere. (b)-(d) plan-view diagrams showing the LP, SP and SD strokes.

### 2.2.2 Material properties

The conductivity of the tissues used in the simulations was obtained from Gabriel et al (1996) and are given in table 1. All tissues were assumed to be isotropic. For small organs such as the eye, which contains a substructure of tissue types, a single homogeneous domain was considered to represent the organ and the conductivity was taken as a weighted average of that of substructures. The stroke volume was considered to consist of 75% blood and 25% brain tissue and the conductivity was calculated as a weighted average of the two (table 1, last 2 rows). In the practical simulations presented in the paper we set \( \varepsilon = 0 \), clearly this
represents another approximation, which we justify based on the comparison with the FEM solution of the vector wave equation presented in Zolgharni (2010).

The reason for adopting this approximation is that it allows a stationary iterative solver to be used for solving the linear system of equations. For FD methods, stationary iterative solvers can be implemented without the need to assemble the large matrix. Clearly, this leads to considerable computational savings. If the true values of $\varepsilon$ were included then this would change the system matrix from being symmetric positive definite to being complex symmetric. For such matrices, the convergence of stationary iterative solvers can no longer be guaranteed and for the values of $\varepsilon$ corresponding to the materials listed in table 1, convergence was not obtained. By adopting an alternative iterative solution technique (or a direct approach) linear systems with complex matrices can of course be solved, but this would require the assembly and storage of a large matrix and therefore would have substantial negative impact on the computational footprint of the FD algorithm. As the computational saving was one of the main reasons for adopting the FD algorithm this approach was not pursued here.

### Table 1. Number of elements in each tissue domain and assigned conductivities at 1 and 10 MHz and the difference between these two conductivities, $\Delta \sigma$. a: number of elements is for the pair of such organs. b: considered as air.

<table>
<thead>
<tr>
<th>Tissue</th>
<th>Number of elements to model the tissue</th>
<th>Conductivity at 1 MHz (S m$^{-1}$) TLM mesh</th>
<th>Conductivity at 10 MHz (S m$^{-1}$)</th>
<th>$\Delta \sigma$ (S m$^{-1}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Muscle</td>
<td>109,607</td>
<td>0.503</td>
<td>0.617</td>
<td>0.114</td>
</tr>
<tr>
<td>Skull</td>
<td>48,652</td>
<td>0.057</td>
<td>0.083</td>
<td>0.026</td>
</tr>
<tr>
<td>CSF</td>
<td>15,390</td>
<td>2.000</td>
<td>2.002</td>
<td>0.002</td>
</tr>
<tr>
<td>Grey matter</td>
<td>18,034</td>
<td>0.163</td>
<td>0.292</td>
<td>0.129</td>
</tr>
<tr>
<td>White matter</td>
<td>45,748</td>
<td>0.102</td>
<td>0.159</td>
<td>0.057</td>
</tr>
<tr>
<td>Ventricles</td>
<td>1,682</td>
<td>as CSF</td>
<td>as CSF</td>
<td>as CSF</td>
</tr>
<tr>
<td>Spinal cord</td>
<td>1,104</td>
<td>0.133</td>
<td>0.225</td>
<td>0.092</td>
</tr>
<tr>
<td>Optic nerve$^a$</td>
<td>65</td>
<td>0.130</td>
<td>0.223</td>
<td>0.093</td>
</tr>
<tr>
<td>Eye ball$^a$</td>
<td>644</td>
<td>1.127</td>
<td>1.200</td>
<td>0.073</td>
</tr>
<tr>
<td>Nasal cavity$^b$</td>
<td>1,639</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Auditory meatus$^{a,b}$</td>
<td>327</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Olfactory organ$^b$</td>
<td>211</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Blood</td>
<td>-</td>
<td>0.822</td>
<td>1.097</td>
<td>0.275</td>
</tr>
<tr>
<td>Stroke (blood/white matter)</td>
<td>-</td>
<td>0.642</td>
<td>0.863</td>
<td>0.221</td>
</tr>
<tr>
<td>Stroke (blood/grey matter)</td>
<td>-</td>
<td>0.657</td>
<td>0.896</td>
<td>0.239</td>
</tr>
</tbody>
</table>

#### 2.3 The inverse problem

The true inverse problem for MIT consists of the determination of the distributions of the material parameters in Maxwell’s equations for a set of given set of measured field quantities on part of the boundary. In our approach, we assume that we can replace the true forward problem by (1) and therefore our inverse problem simplifies to the determination of the distribution of $\sigma$ for given known current sources and voltage measurements.

Simulations were carried out for the head with the haemorrhage present. Firstly, the forward problem was solved at 1 MHz and the MIT signals recorded; we denote by $\mathbf{V}_f = (V_{1,1}, V_{1,2}, ..., V_{1,N_s}, ..., V_{N_e,N_s})$ the “reference” set of secondary voltages produced in the $N_s$ sensor coils when each of the $N_e$ exciter coils are
excited in turn. Secondly, the process was repeated but at 10 MHz and the new signals were computed; we denote by \( V_{f_2} = (V_{1,1}, V_{1,2}, ..., V_{1,N_s}, ..., V_{N_e,N_s}) \) the “data” set of secondary voltages. The phase differences

\[
(\Delta \Phi)_{i,j} = \frac{(V_{f_2})_{i,j} - (f_2/f_1)^2 (V_{f_1})_{i,j}}{(V_p)_{i,j}} \tag{4}
\]

were computed for \( i = 1,2,\ldots,N_e, \ j = 1,2,\ldots,N_s \). In this expression, the voltages \( V_p = (V_{1,1}, V_{1,2}, ..., V_{1,N_s}, ..., V_{N_e,N_s}) \) are the primary voltages at frequency \( f_2 \), that were recorded in the absence of the head. The phase difference is proportional to the change in conductivity between \( f_1 \) and \( f_2 \) (Brunner et al 2006, Zolgharni et al 2008).

In order to avoid committing an inverse crime, the sensitivity matrix, \( S \), was computed using a different discretisation (2.5 mm cubic mesh comprising 243,083 elements) from that used for the forward problem (2 mm cubic mesh comprising 474,897 elements). The sensitivity matrix was computed by setting the conductivity to a uniform value (1 S m\(^{-1}\)) throughout the head. Its entries correspond to (Hollaus et al 2004, Ktistis et al 2008):

\[
(S)_{i,b+(a-1)N_s} = \frac{E_a^b |_i}{(V_p)_{a,p}} \tag{5}
\]

To compute the entry \((S)_{i,b+(a-1)N_s}\) of the sensitivity matrix, two solutions of the forward problem at frequency \( f_2 \) are required. The quantity \( E_a^b |_i \) is the electric field evaluated in voxel \( i \) when the exciter coil \( a \) is activated, and \( E_b^b |_i \) is the electric field evaluated in the same voxel when the sensor coil \( b \) is activated as an exciter. The system sensitivity matrix, \( S \), has as many rows as there are voxels in the volume (243,083) and as many columns as there are coil combinations (784 for the helmet). Each row of the sensitivity matrix, which represents the contribution of one coil combination, was normalized to the primary signal in order to be compatible with equation (4). From a truncated Taylor series it follows that

\[
\Delta \Phi = S \cdot \Delta \sigma \tag{6}
\]

where \( \Delta \sigma \) is the change in the conductivity distribution between two frequencies, i.e. the image. The system is under-determined and ill-conditioned. The approximate solution to the inverse problem was, therefore, obtained by means of the single-step Tikhonov-regularized pseudo-inverse (Lionheart 2001):

\[
\Delta \sigma = S^T (S S^T + \lambda I)^{-1} \Delta \Phi \tag{7}
\]

where \( I \) is the identity regularization matrix, and \( \lambda \) is the scalar regularization parameter.

2.3 Simulated errors

2.3.1 Phase noise

Different levels of Gaussian phase noise (up to 20 m\(^\circ\) standard deviation) were added to the simulated MIT phase changes in order to test the effect of measurement noise on the reconstructed images.

2.3.2 Systematic errors
It is widely appreciated that MIT image reconstruction will be improved by introducing as much *a-priori* information as possible and one example of this is to determine the boundary of the eddy-current region, in this case the shape of the head, by some independent means such as by optical shape scanning (Wan-Daud *et al* 2003). The sensitivity matrix will then be computed for this known region. Accurate calibration of the optical method will be important and so will accurate registration of the optically-determined boundary with the known geometry of the MIT array. Inevitably there will be errors in these processes.

In order to examine the effect of such inaccuracies, two types of geometrical systematic errors were simulated. The first simulated a mis-registration equivalent to a displacement of the head relative to the helmet, separately in x, y and z directions (figure 3a). The second involved a simple scaling error simulated by an expansion or contraction of the entire head (figure 3b). As the coils do not form part of the FD discretisation, but instead are perfect circles whose coordinates and orientation are specified separately, it is very easy to model these geometrical changes. A shift of the head was introduced by altering the coordinates of all the coils by a fixed amount, whilst leaving the mesh unchanged. Similarly, an expansion or contraction of the head was introduced by altering the FD mesh size whilst leaving the coils unchanged. For image reconstruction, the sensitivity matrix was computed using the changed (‘erroneous’) boundary of the head. The simulated MIT measurements at 1 and 10 MHz were computed using the original (‘true’) head boundary.

![Figure 3](image.png)

**Figure 3.** Exaggerated geometrical errors: light pink and dark blue colours show the ‘true’ and ‘erroneous’ boundaries, respectively. (a) displacement in y-direction. (b) contraction.

3. Results

3.1 Noiseless reconstructed images

We deal first with the results for the simulations involving the LP stroke; results for the SP and SD strokes will be presented in section 3.4. The value of the regularisation parameter, $\lambda$, (equation 7) was optimised by computing the image error, $E_1$:

$$E_1 = \frac{\|\Delta\sigma_{\text{true}} - \Delta\sigma_{\text{rec}}\|}{\|\Delta\sigma_{\text{true}}\|}$$

where $\Delta\sigma_{\text{true}}$ is the true distribution of conductivity rise (1-10 MHz) entered into the forward model and $\Delta\sigma_{\text{rec}}$ is the reconstructed distribution, i.e. the image. Throughout, $\|\|$ denotes the standard $L_2$ norm and values are plotted as percentages. Note that the target ($\Delta\sigma_{\text{true}}$) and image ($\Delta\sigma_{\text{rec}}$) have different discretisations. For computing $E_1$, the target was interpolated onto 2.5 mm voxels, as if it had been simulated using this mesh.

In evaluating the norms, the integration was carried out over the volume of the head superior to the base of the brain. The optimal $\lambda$, that which gave the minimum value of $E_1$, was $2.5 \times 10^{-9}$, $2.5 \times 10^{-9}$ and $7.5 \times 10^{-10}$ for MK1, H100 and H120, respectively (figure 4). The minima exhibited by the curves were broad, indicating that there was no sharp optimisation of $\lambda$. The values of the minima were very similar; 64.3%,
63.1%, and 63.3% for MK1, H100, and H120, respectively.

![Figure 4. Error, $E_1$, in reconstructed images as a function of $\lambda$, for the three MIT arrays simulated.](image)

Images ($\Delta \sigma_{\text{rec}}$) reconstructed using the optimal $\lambda$ in each case and three cross sections from the volume images were extracted for display (figure 5). A feature due to the stroke is evident on the images from the MK1 array, but is displaced outwards towards the surface (column 2, rows 1 and 2). The stroke is better visualised with the helmet (columns 3 and 4). For H100, the feature has amplitude 0.15 S m$^{-1}$ (c.f. true value 0.22 Sm$^{-1}$). Increasing the radius of the helmet to 120 mm (H120) has the advantage of reducing the artefacts of raised image value occurring near the coils (columns 3 and 4, row 3), but at the expense of reducing the amplitude of the stroke feature to 0.14 S m$^{-1}$ (columns 3 and 4, rows 1 and 2). For comparison, images reconstructed from data simulated with stroke absent for H100 are shown (column 5); for this, the optimal $\lambda$ was $5.0 \times 10^{-9}$. All three coil configurations show an artefact of raised image value at the nape of the neck (row 3). Because of its better visualisation of the stroke feature, only H100, the helmet of 100 mm radius, will be considered in the remainder of this article.
3.2 Noise

By adding different level of phase noise to the simulated data, the image error due to the noise was evaluated as $E_2$:

$$E_2 = \frac{\| \Delta \sigma_{\text{noisy}} - \Delta \sigma_{\text{noiseless}} \|}{\| \Delta \sigma_{\text{noiseless}} \|}$$

where $\Delta \sigma_{\text{noisy}}$ and $\Delta \sigma_{\text{noiseless}}$ are the images reconstructed with and without noise. Again, the integration was carried out over the volume of the head superior to the base of the brain. $E_2$ thus is a measure of the spurious content in the image due to the noise, as a percentage of the true image content, and increases roughly in proportion with the phase noise added to the simulated measurements (figure 6). Examples of images are shown in figure 7, including two particular noise levels: 17 m°, the level in the practical Cardiff MK1 data collection system (Watson et al 2008) and 1 m°, the level achievable in the new electronics described by Wee et al (2008). Comparing with the noiseless image (figure 7, column 1), the image is hardly degraded by a noise level of 1 m°, and the stroke remains clearly visible, whereas for 17 m°, the noise dominates the image. Of course, the noise artefacts will change for every run of the random number generator, but qualitatively the images will remain similar. The artefacts in the image can be reduced by increasing the regularisation parameter, $\lambda$, but at the disadvantage of blurring the stroke feature.

By inspection of the images in figure 7, it would appear that an acceptable noise level would be between 1 and 5 m° and could reasonably be set at 3 m°. This leads to an acceptable value of the error measure, $E_2$, of approximately 19% (figure 6).
3.3 Systematic errors

Displacement of the head in the positive x direction, produced artefacts which appear as increased values on the surface that faces towards the negative x direction, and, decreased values on the surface that faces towards the positive x direction (figure 9, column 2, rows 1 and 2). A displacement in the opposite direction produced the opposite effect (figure 9, column 3, rows 1 and 2). Similarly, displacements of the head in the positive and negative y directions produced increased and decreased values adjacent to the surfaces facing these directions (figure 9, columns 4 and 5, row 1). No random noise was included in any of these simulations.

Contraction of the head (scaling error) produced increased values near the surface of the head (figure 9, column 6). This is to be expected; in contracting of the geometry, a layer of conductive material is removed.
from the periphery. Consequently, the signal induced by the omitted parts is also removed from the sensitivity matrix. This contribution in the signals has to be compensated by higher values of conductivity in the images which appear as raised artefacts on the boundary. Expansion of the head produced a peripheral lowering of image values (figure 9, column 7).

For different displacements in the x, y and z directions and different magnitudes of the scaling error, the artefacts on the images were again quantified by evaluating $E_2$, using equation 9, but with $\Delta \sigma_{\text{noisy}}$ replaced by the image reconstructed from signals simulated with a displacement or scaling error present. This time, $E_2$ is a measure of the image content due to the systematic errors expressed as a percentage of the true image content, and is plotted in figure 9.

Applying the same acceptance criterion as for the level of random noise, i.e. $E_2 < 19\%$, indicates that the mis-registration displacement error should be no more than 3-4 mm, and the size scaling error should be no more than about 3-4%.
3.4 SP and SD strokes

For the small peripheral and small deep stokes, the value of $\lambda$ was optimised in the same way as before by minimising the error, $E_1$. For both, the optimal $\lambda$ was the same as with the stroke absent, $5.0 \times 10^{-9}$. The images are shown in figure 10 with the colour-bar reduced in order to make the features more visible. For comparison, the images for the normal head are also displayed on the new colour scale. The SP stroke produces a noticeable left-right asymmetry in the images, but the limited spatial resolution does not allow it to be well visualised even on these noiseless images. The SD stroke cannot be visualised at all due to the artefacts that already on the image of the normal head.

![Figure 9. Image error, $E_2$, for different displacements of the head or percentage scaling.](image)

![Figure 10. Images from data simulated for H100 with the small peripheral and small deep strokes and the normal head, without the stroke.](image)
4 Discussion

Using a realistic model of the head, a finite-difference method was employed to simulate MIT measurements for a haemorrhagic stroke in the brain. Two different types of coil array were simulated: a conventional annular array, scanned along its axis and a new hemispherical array in the form of a helmet to be placed over the head. The hemispherical array was intended to minimise the distances between the coils and the brain and to maximise the sensitivity to this region of interest.

Frequency-difference images were reconstructed using a single-step Tikhonov method and produced the distribution of the change in conductivity between 1 and 10 MHz. For this particular model and image reconstruction algorithm, the results showed that for noiseless data, a simulated large peripheral stroke (volume 50 ml) could be visualised by both types of array, but better by the hemispherical array. By adding 1 m° of phase noise to the simulated measurements, the stroke was still well visualised on the images; this is the noise level currently achievable in practice (Wee et al 2009). An error measure of the contribution of the noise to the image was computed and it was concluded that a tolerable phase noise level for imaging the large peripheral stroke was about 3 m°.

Two types of errors in the a-priori information on which computation of the sensitivity was based were simulated. The first was a displacement of the head and the second was a size-scaling error. These errors produced artefacts near the periphery of the images which, when positive, could either masquerade as a haemorrhage or when negative, could cancel a feature due to a genuine haemorrhage. These systematic errors on the image were quantified using a similar error measure. It was concluded that the displacement error must be no more than 3-4 mm and that the scaling error must be no more than 3-4%. We have assumed that these related to the intrinsic errors in the a-priori determination of the boundary information. Gursoy and Scharfetter (2009) in a related study showed similar artefacts on the images and demonstrated that these could be corrected by tracking the movement of the patient relative to the coil array throughout the data acquisition.

For a smaller stroke (volume 8 ml), especially when located more centrally in the brain, visualisation was poor. One reason for this is the low spatial resolution of the images. Another reason is that all the tissues in the head increase in conductivity with frequency and produce a background of changes against which the stroke, albeit of greater conductivity change (see table 1), must be detected. The images of the normal head, without the stroke, demonstrate this background (figure 5, column 5 and figure 10, column 3). Even within each tissue type, there are non-uniformities of image value, e.g. most markedly near the coils and at the nape of the neck (e.g. figure 10, row 3), but also within the white matter of the brain (figure 10, row 1, column 3). This difficulty can be contrasted with time-difference imaging (after-stroke relative to before-stroke) where only the stroke region changes and even these small strokes are easily visualised (Zolgharni et al 2009a). Improvements in image reconstruction for frequency-difference imaging are necessary. The spatial resolution could be improved by acquiring a larger number of independent measurements, such as by scanning the annular array through more axial positions but the helmet is likely to be a more practicable arrangement for clinical application. The use of more than two frequencies in order to define the ‘frequency signature’ of the stroke as distinct from that of the other head tissues may be of advantage.

This study has concentrated on haemorrhagic stroke. An MIT system would have greater clinical usefulness if able to identify ischaemic stroke too. This will be more difficult because the conductivity changes are due to cell swelling and reduction of the intracellular space and affect the conductivity most at low frequencies. Holder (1992) has however shown in an animal model that the changes were by as much as 50% at a frequency of 50 kHz. Even so, this is much lower than the frequencies simulated here (≥ 1 MHz). Some MIT researchers are now designing hardware for operation down to such frequencies (Brunner et al 2006, Zheng et al 2009). In a recent report, Gonzales et al (2009) measured the bulk conductivity of the heads of rats using an inductive method. Large phase differences at frequencies of 10 MHz and above were observed in the animals in which cerebral ischaemia had been induced, relative to a control group. However,
caution is necessary, for the largest increases were recorded some 12 hours after the induction of ischaemia and as the authors themselves point out, were probably related to structural damage of the cells. Within the first 2 hours, the period relevant for rapid identification of stroke type, the phase changes were much smaller in magnitude and negative in direction although the scatter in the experimental data was large.

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