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Quantification of Intraventricular Hemorrhage with Electrical Impedance Tomography Using a Spherical Model

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Abstract

We have developed a robust EEG based current pattern which shows promise for detection of intraventricular hemorrhage (IVH) in neonates. Our reconstructions to date are based on a layered spherical head model. In this study, the current pattern was used to gather data from three realistic shaped neonatal head models and a physical phantom based on one of these models. We found that a sensitivity matrix calculated from a spherical model gave us satisfactory reconstructions in terms of both image quality and quantification. Incorporating correct geometry information into the forward model improved image quality. However, it did not improve quantification accuracy. The results indicate that using a spherical matrix may be a more practical choice for monitoring IVH volumes in neonates for whom patient-specific models are not available.

Keywords

electrical impedance tomography; intraventricular hemorrhage; neonate; forward model

1. Introduction

Intraventricular hemorrhage (IVH) is intracranial bleeding that accumulates inside the ventricles, spaces in the brain compartment that are normally filled with cerebral spinal fluid (CSF). IVH is particularly common in very low birth-weight babies (those weighing less than 1 500 g). IVH affects 35–50% of very premature human infants to some degree and is a significant cause of death and disability (York and DeVoe 2002). EIT, as a non-invasive imaging technique, offers the potential to monitor bleeding continuously. In conventional EIT measurements, currents are injected into a volume through one pair of an electrode array, and the data consists of differential voltages measured between other array electrodes. The conductivity distribution can be reconstructed using a sensitivity-based method. The sensitivity matrix can be formulated using a forward model (Yorkey et al. 1987).

In our previous study using spherical head model-based reconstructions (Tang *et al.* 2010), we showed that an EEG-based current pattern (figure 1) had advantages over the conventional EIT ring-based electrode layout and adjacent measurement pattern in terms of detection and quantification of bleeding within regions of interest inside the ventricles. The enhanced performance of our EEG-based electrode layout was demonstrated with homogeneous and layered spherical models and when the EEG-based method was used to reconstruct data generated from models with realistic external geometry and internal conductivity distributions.

Previous studies demonstrated that incorrect estimates of boundary shape reduce the quality of reconstructed EIT images and result in artefacts being introduced (McInerney and Terzopoulos 1996). Incorporating an accurate forward model instead of using circular or spherical forward models has been a popular topic in EIT brain and lung imaging (Bagshaw *et al.* 2003, Liston *et al.* 2004, Borsic *et al.* 2001, Fan *et al.* 2009); and in inverse EEG and MEG imaging (van Uiter and Johnson, 2002, von Ellenrieder *et al.* 2008, Baillet *et al.* 2001). Meeson *et al.* (1995) demonstrated that inclusion of bony structures in forward models could improve image quality in the pelvis. Abascal *et al.* (2008) demonstrated the improvement in image quality by including anisotropy into a forward model used for reconstructions. However, realistic models need to be used carefully, because with inaccurate prior information, they may yield images worse than reconstructed with a simple forward model (Liston *et al.* 2004).

Real neonatal heads differ from spherical models in many aspects, such as their external boundary shape and internal anatomical structures. Because of the ill conditioning of the EIT problem, these differences will introduce errors into reconstructed images when the spherical-based reconstruction algorithm is applied to data collected from real patients. In practice, head geometry varies from patient to patient, which makes it difficult to accurately specify the forward model. In our application, use of patient-specific models is often not practical, due to the difficulties collecting MRI images from unstable premature neonates. In addition, the neonatal head can vary in shape depending on posture so that even if a patient-specific model were to be created its relationship to the head shape from which data is collected is uncertain. It is therefore necessary to investigate the following question. What is the most robust reconstruction model to use in circumstances where the accuracy of the forward model is unclear? In this study, we compared images reconstructed using both spherical and head-shaped forward models and sensitivity matrices, and evaluated the necessity of using an accurate forward model for the purpose of detecting and quantifying intraventricular bleeding in neonates.

2. Materials and Methods

Four finite element meshes were used in this study. They were generated from a homogeneous spherical model (US mesh), a homogeneous realistic head-shaped model (UM mesh), another homogeneous realistic head-shaped model (UG mesh), and the layered G model (LG mesh). The LG mesh included brain, neonatal skull, cerebrospinal fluid, fat and scalp structures. Two sensitivity matrices (the S_{SP} matrix and S_M matrix) were formulated from US and UM meshes respectively. Noisy simulated data was also generated from the UM, UG, and LG meshes and from phantom tank based on the M model (PM). Further details of the operations performed are given below.

2.1. Sensitivity Matrices

Two forward models were used to formulate sensitivity matrices. One was a spherical model with unit radius and homogeneous conductivity distribution (the US model, Tang *et al.* 2010). The SP model was meshed into 21 896 tetrahedral elements. We then implemented the 16-electrode EEG layout on this model based on the spherical coordinates of the 10–20 electrode locations shown in figure 1. All currents applied were returned via the C_z electrode, and voltages between adjacent electrodes (in terms of electrode numbering (figure 1b)) were measured. The current pattern therefore involved 15 current positions and a total of 182 voltage measurements. Details of the EEG-based electrode addressing protocol can be found in Sadleir and Tang (2009). The second forward model was a neonatal head model with realistic head geometry and homogeneous conductivity distribution (the UM model). This model was constructed from MRI images of a normal term neonate. The model was meshed into 45 702 tetrahedral elements with 8 703 nodal points. Electrode locations for the

UM model were chosen to be as similar as possible to those used on the spherical model, while adapting to the realistic head's orientation. In addition, in the UM model the C_z electrode was shifted slightly from the central axis to determine the effect of electrode location variation on the model's symmetry.

2.2. Data Generation

We gathered simulated bleeding data using three head-shaped finite element models (US, UG and LG) and one head-shaped phantom (PM).

The first one (the UM model) (figure 2(a)) had a boundary geometry the same as the model we used to formulate the S_M sensitivity matrix. The mesh data can be organized into a file with STL format or MPHTXT format, and then imported into COMSOL (Comsol, Burlington MA, USA) for the purpose of geometry visualization and numerical simulation. The background conductivity was assigned to be homogeneous with the conductivity of CSF (1.3 S/m) (Oostendorp *et al.* 2000). In this study, we created two bleeding sites at positions corresponding to the centers of the left and right ventricles, respectively. Bleeding was simulated by manually setting the corresponding elements of the finite element forward model to the conductivity of blood (0.67 S/m) (Geddes and Baker 1967). The total volume of the model was 791 ml. The centers of the ventricles were determined to be 18 mm above the anatomical center and spaced laterally 18 mm apart about this point. To simulate different volumes of intraventricular hemorrhage, we simulated 6 different cases on each side with total blood volume increasing linearly from 0.5 ml to 3 ml.

The second realistic geometry model used in this study (the G model) (figures 2(b–c)) was provided by researchers at the University of Gent in Belgium. It was constructed from the MRI data from a 39 week gestational age patient who suffered from asphyxia. The original 3D image had a dimension of $256 \times 256 \times 129$, with each pixel size $0.7 \times 0.7 \times 0.63$ mm. Five major structures were segmented from the images, including CSF, brain tissue, skull, fat and scalp (figure 2(c)). To acquire more accurate FEM solutions, we converted the whole structure to a tetrahedral mesh containing 23920 nodes and 126432 tetrahedrons. The purpose of using this model was to test our two sensitivity matrices on a different 'patient', whose geometry matched neither one of the forward models. In the beginning of this study, we were primarily interested in the effects from boundary shape. Therefore, we removed the internal structures by setting the background homogeneous with conductivity value 1.3 S/m (UG model) and selected two bleeding sites at the ventricle centers. Ventricle center positions were determined using the original MRI data. We determined that the two ventricles were 44 mm above the base and 17 mm apart. We simulated six different cases each side with blood volumes increasing linearly from 0.5 ml to 3 ml. The 16 EEG electrodes were also incorporated on the scalp according to their spherical positions. To make the model more realistic we restored all internal structures into the model (LG model). The positions and volumes of simulated bleeding were the same as used in the UG model.

To make our data more realistic, we added noise to all simulated data. We chose to use 70dB Gaussian noise, which was determined from the SNR levels of practical EIT systems (Oh *et al.* 2007, Murrieta-Lee *et al.* 2004). We added noise to model data by first measuring the signal power, and then adding 70 dB noise using the MATLAB function 'AWGN'.

To test our methods in the presence of realistic noise, we constructed a plastic head-shaped phantom of the M model (PM), using a 3D printer (Dimension, Inc., MN, USA). The stages of phantom construction are illustrated in figure 3. The surface mesh was first extracted from the M model (figure 2(a)), with the bottom surface removed (figure 3(a)). The mesh was therefore hollow at the 'neck'. We then produced a copy of the mesh at 90% of its original scale, and placed it inside the original mesh to create two concentric shells. By

connecting the two surface meshes at the neck with an annulus of triangles, we created a closed shell structure with a triangular surface mesh (figure 3(b)). The size of the solid model was increased before importation into the 3D printer because of manufacturing constraints of the 3D printer. As a consequence, the PM phantom had the same boundary shape as the M model, but a total volume was 1628 ml, about twice the original model's volume. The phantom had 16 stainless steel electrodes attached as shown in figure 3(c), the same electrode locations as used in the UM model. A 0.9% saline solution (the conductivity of which was approximately 1.3 S/m, the conductivity of CSF) was used as the phantom background. Bleeding was simulated using gel anomalies made of TX151, agar and saline (Sadleir *et al.* 2009). The TX-151 gel conductivity was adjusted to 0.67 S/m by adjusting the mass of salt added to TX-151 formulations to 3 g/l. We prepared 6 cylindrically-shaped anomalies with volumes from 1–6 ml. Following the protocol used to generate UM data, we placed gel anomalies at the location of left and right ventricle centers, which were determined to be 23 mm above the anatomical center and 23 mm apart from each other. Anomalies were placed accurately within the phantom using a 3D positioner (Velmex, Inc., NY, USA). We collected data using a KHU Mark1 16-electrode EIT system provided by the IIRC at Kyung Hee University, Korea (Oh *et al.* 2007). We chose to use a single frequency of 10 kHz and a constant current output of 1 mA. Ten data sets were collected and averaged as a reference before introduction of anomalies. In each of the 12 experiments, ten data sets were collected and averaged to form the data for that volume of bleeding.

2.3. Reconstruction, Quantification and Image Quality

In EIT difference imaging, the conductivity perturbation can be related to the changes on boundary voltage measurements via a sensitivity matrix S ($\Delta V = S\Delta\sigma$). A truncated singular value decomposition method (TSVD) (Xu 1998) was used to regularize the pseudo-inversion of S . We chose a truncation value of 50 based on L-curve inspection. This truncation was used for all reconstructions in this study. Quantification was assessed with a characteristic parameter called the quantification index (QI), which has been found to correlate well with volumes of blood-like anomalies using 2D disk-based sensitivity

matrices (Sadleir *et al.* 1998, 2008). QI is defined as $QI = \sum_{i=1}^{ne} \Delta\sigma_i v_i$, where ne is the total number of elements in the mesh, $\Delta\sigma_i$ is the conductivity change reconstructed in the i^{th} element and v is the volume of each element. We evaluated image quality by estimating the resolution R . This was calculated by estimating the portion of volume that contains voxels having reconstructed values more than half of the maximum value, then taking the cube root

$$(R = \sqrt[3]{\frac{V_{HM}}{V_0}}).$$

3. Results

3.1. Image Quality

Reconstructions of anomaly 1 (0.5 ml) are shown in figure 4 for the UM model (figure 4(a)), UG model (figure 4(c)) and LG model (figure 4(d)). Only reconstructions of anomaly 6 (6 ml) are shown for PM phantom data (figure 4(b)) because reconstructed images of its smallest anomaly (1ml) were severely contaminated by noise. Note that the overall volume of the PM phantom was over twice that of the computational models. In figure 4, the images are presented as follows. The first row (S_M matrix) and the second row (S_{SP} matrix) show the reconstructed images of right-located anomalies. The third row and fourth rows show images of the corresponding left-located anomalies. The first column shows axial plots of reconstructions and the second column shows sagittal plots (both centered on the anomaly). The third column shows isosurface plots based on the half maximum conductivity identified

in the reconstruction. This provides a straightforward 3D view of the reconstructed images. Left and right anomaly reconstructions were compared in each case to demonstrate asymmetry, and image resolutions of all the reconstructed anomalies are shown in table 1. As expected, the reconstructions from UM model data using the S_M matrix had consistently better image resolution than reconstructions using the S_{SP} matrix. The S_M matrix also showed an advantage over the S_{SP} matrix in reconstructing PM phantom data. However, the S_M matrix did not show a consistent advantage in reconstructing data from the UG model. Instead, S_{SP} reconstructions had consistently better image resolutions (average $R = 0.1887$) than the S_M reconstructions (average $R = 0.2168$) for the right side, although S_M reconstructions showed better image qualities (average $R = 0.1836$) than the S_{SP} cases (average $R = 0.2929$) for the left side. S_M reconstructions for the LG model data showed better image resolutions in most cases, except for blood volume 1 on the right side.

3.2. Quantification Accuracy

Quantification indices for the six different anomaly sizes on the left side were calculated for each of the four models (figure 5). The results for the anomalies on the right side were similar (they are not presented here). The quantification performances of the two matrices were almost identical for simulated UM model data. The S_M matrix had a relatively better quantification accuracy for PM phantom data (average error = 0.0025 S.cm^2), compared with the S_{SP} matrix (average error = 0.0034 S.cm^2). The S_M matrix did not show any significant advantage over the S_{SP} matrix for data from UG and LG models.

4. Discussion

Our earlier studies showed that the sensitivity and selectivity patterns for the S_M sensitivity matrix were similar to those obtained from the spherical model (Sadleir and Tang 2009). Studies using a layered realistic geometry model showed the possibility of using a spherical forward model to reconstruct images using data collected from a real head (Tang *et al.* 2010). In addition, the image quality produced using the EEG current pattern has been shown to be comparable with those found using similar approaches in the literature (Tang *et al.* 2010). This study, using the three homogeneous models (the UM model, PM phantom, UG model) and one layered model (LG model), further proved the potential of using spherical model as a generalized forward model for different patients.

EIT image quality is highly dependent on the forward model. Fan *et al.* (2009) found that human lung reconstruction was improved by using a boundary model developed from 3D CT scan data. In our study, we found that better image resolutions were obtained using the S_M matrix when using both simulated and phantom data from model M. This confirmed the findings from early studies, since the model used to construct S_M model shared an identical boundary shape and electrode locations with the UM model and PM phantom. When reconstructing data from model G, the S_M matrix produced superior results for left-located anomalies only. We believe this can be explained by the asymmetry of the C_z electrode placement in the EEG electrode layout. In the M model, the C_z electrode was placed to the left of the head apex and therefore produced relatively larger sensitivity and selectivity in left ventricular regions (Sadleir and Tang 2009). However, the advantage for the S_M matrix was not sustained for anomalies positioned on the right, and here the S_{SP} matrix showed consistently better image resolutions, as shown in figure 4(c).

Kolehmainen *et al.* (1997) and Blott *et al.* (1998) concluded that the locations of electrodes and the boundary shape of the forward model contributed the most errors to the reconstructed images. The three homogeneous models used in this study also enabled us to investigate the effect from boundary geometries alone. The LG model enabled us to compare the performance of the two sensitivity matrices on a more 'realistic' patient. An

interesting finding here was the relative improved performance of the S_M matrix compared to its performance on the LG model, although it did not show much advantage for small blood volumes. The results in this study indicated that the S_M matrix produced better images for the correct geometry, but conferred no advantage over the S_{SP} matrix for the wrong geometry. Future work should include collecting data from real patients to validate these findings. In addition, previous work has shown that a multilayered sensitivity matrix gave the best results in simulation (Bagshaw *et al.* 2003). Therefore, a sensitivity matrix derived from a multilayered neonatal head model should also be tested and compared with the performance from the homogeneous sensitivity matrices.

The S_M matrix showed no better performance than the S_{SP} matrix in term of quantification. Figure 5(a) shows that the S_{SP} matrix could be calibrated to quantify the anomalies equally as well as the S_M matrix, and these QIs matched the ideal QIs. Use of the S_M matrix did not show a consistent advantage in terms of quantification of reconstructed PM phantom data (figure 5(b)). Another interesting observation was that the QIs calculated from the S_{SP} matrix showed smaller error bars in most cases, which indicates that S_{SP} matrix reconstructions may have advantages over S_M matrix reconstructions in noisy environments. Both matrices quantified data from UG model data well (figure 5(c)). In this case, where the object geometry matched neither sensitivity matrix, the S_M matrix did not show any advantage over the S_{SP} matrix. In addition, QIs calculated from the S_{SP} matrix also showed smaller error bars in most cases. When considering quantification results from the LG model (figure 5(d)), we found that the QIs from the S_M matrix showed slightly better accuracy with larger blood volumes. However, this did not seem to give a significant advantage for the detection of grade II IVH (blood filling less than half the ventricle).

5. Conclusion

We compared the performance of two sensitivity matrices (S_{SP} and S_M) using different head models. It is evident that the matrix developed from a realistic-shaped forward model does not guarantee image quality when the subject has mismatched boundary shape and electrode locations. Moreover, the S_{SP} matrix performed better in quantification of phantom experiment data. All our observations indicated that using a simple spherical matrix may be adequate for monitoring IVH quantities in neonates.

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Figure 1.
A three dimensional spherical model showing the 16 EEG electrode layout and the EEG current pattern.

Figure 2.
(a) the M model. (b) the G model and (c) a cross-sectional image of the layered G model (LG).

Figure 3.
Procedures to construct the M phantom.

Figure 4.

Reconstructions of anomalies obtained using the S_M and S_{SP} matrices using the data from four models. Subplots are (a) UM model, (b) PM phantom, (c) UG model, (d) LG model. In the first and second rows, anomalies are on the right, and in third and fourth rows anomalies are on the left. The first column in each subplot shows an axial (transverse) slice of the reconstruction, centered on axial center of anomalies. The second column of each subplot shows a sagittal slice, centered on sagittal center of anomalies. The third column of each subplot shows an isosurface rendering of the reconstructed image, with the isosurface at the half maximum reconstructed conductivity. Images are of reconstructions of 0.5 ml anomalies in subplots (a), (c) and (d), and 6 ml in subplot (b).

Figure 5. Quantification indices for the images reconstructed with the S_M matrix and S_{SP} matrix. Data was collected from (a) UM model, (b) PM phantom, (c) UG model, (d) LG model. All anomalies were on the left.

Table 1

Resolution values of the reconstructions for all anomaly volumes.

	S Matrix	Left						Right					
		1	2	3	4	5	6	1	2	3	4	5	6
UM	SP	0.196	0.248	0.260	0.258	0.252	0.254	0.235	0.245	0.243	0.238	0.245	0.246
Model	M	0.184	0.192	0.183	0.183	0.181	0.180	0.211	0.192	0.194	0.205	0.204	0.201
PM	SP	N/A	0.311	0.302	0.263	0.265	0.270	N/A	0.268	0.252	0.270	0.238	0.302
Phantom	M	N/A	0.123	0.184	0.180	0.193	0.195	N/A	0.161	0.177	0.164	0.201	0.187
UG	SP	0.196	0.293	0.306	0.301	0.312	0.310	0.182	0.176	0.183	0.189	0.183	0.187
Model	M	0.176	0.202	0.195	0.193	0.190	0.190	0.209	0.193	0.194	0.189	0.204	0.209
LG	SP	0.181	0.181	0.178	0.198	0.207	0.214	0.203	0.232	0.212	0.202	0.216	0.204
Model	M	0.176	0.165	0.160	0.156	0.158	0.158	0.200	0.169	0.148	0.182	0.158	0.180