Incorporating *a-priori* anatomical information into image reconstruction in electrical impedance tomography

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Abstract. Image reconstruction in electrical impedance tomography using the sensitivity theorem is generally based on the assumption that the initial conductivity distribution of the body being imaged is uniform. The technique of image reconstruction using this method is described and reconstructed images are presented. Improvements in image quality and accuracy are demonstrated when accurate *a-priori* 'anatomical' information, in the form of a model of the distribution of conductivity within the region to be imaged, is used to construct the sensitivity matrix. In practice correct *a-priori* information is not available, for example, the conductivity values within the various anatomical regions will not be known. An iterative algorithm is presented which allows the conductivity parameters of the *a-priori* model to be determined during reconstruction.

1. Introduction

The methodology of two-dimensional (2D) electrical impedance tomography (EIT) has been described in detail elsewhere (Barber and Brown 1984, 1990, Brown and Seagar 1987). Electrodes are positioned with equal spacing around the body to be imaged thus defining a plane through the object. Voltage profiles are collected for all drive and receive electrode-pair combinations and images are reconstructed as though the data were from a 2D object. In this work 16 electrodes have been placed around a circular object. Current is driven into the object through two adjacent (drive) electrodes. For each of the 16 drive-electrode pairs, 13 voltage differences between the remaining adjacent non-current carrying (receive) electrodes are recorded. In practice objects are three-dimensional (3D); current cannot be

confined to one plane. However, the reconstruction algorithm usually assumes that the object is 2D. This paper will only deal with proper 2D reconstruction.

Previous investigations of such an approach includes the incorporation of *a-priori* information into the Sheffield filtered backprojection image reconstruction algorithm, which showed some success (Avis et al 1995). Also, Zadehkoochak et al (1991) presented a reconstruction algorithm based on the inversion of the sensitivity matrix associated with a non-uniform conductivity distribution using the singular value decomposition (SVD) method. They did not present any reconstructed images. Zadehkoochak et al (1993) have also investigated the use of *a-priori* information associated with imaging the thorax and reported artefacts in the resulting images. The use of a universal model (a standard model of internal conductivity distribution within the human thorax) has been speculated by Zadehkoochak et al (1993) to be invalid; however, it will been shown that providing the assumed anatomical model is closely matched to the patient's anatomy an improvement in the reconstructed image is achieved.

The conductivity of a region, discretised into small areas or elements, can be written as a column matrix or vector. When this conductivity changes from a reference conductivity distribution σ_{ref} (where each element has units of conductivity (Sm^{-1})) to a conductivity σ_{dat} (where each element has units of Sm^{-1}) it represents a change in conductivity $\Delta\sigma = \sigma_{dat} - \sigma_{ref}$, where $\Delta\sigma$ is a vector of the same size as both σ_{dat} and σ_{ref}. Images of this change in internal impedance distribution can be reconstructed from the resulting change in differential boundary voltages measured in volts ($\Delta v = v_{dat} - v_{ref}$) from a uniform conductivity distribution, where v_{dat} , v_{ref} and Δv are column vectors, usually of a different size from the conductivity vectors; the actual size depending on the number of independent differential boundary voltage measurements. These images of conductivity change can be obtained using a relationship described by a sensitivity matrix (**S**) which is derived using a theorem by Geselowitz (1971). This relation is given by:

$$\Delta \boldsymbol{v} = \boldsymbol{S}\Delta\sigma \qquad (1)$$

where **S** is a sensitivity matrix (usually non-square), $\Delta\sigma$ is a vector containing the changes in conductivity and Δv is a vector containing the corresponding changes in voltage profiles. **S** relates the small conductivity

change within each individual pixel of the image to the corresponding differential boundary voltage change for each and every pixel and each and every drive-receive electrode combination. The relationship between Δ v and $\Delta\sigma$ is often assumed to be linear (Barber and Brown 1990) and thus the elements of **S** are independent of conductivity. **S** is usually calculated by assuming that the initial conductivity distribution is uniform, i.e. all elements within a region to be imaged have the same conductivity value (Barber and Brown 1990) and then calculating the resulting boundary voltage changes due to small perturbations in the conductivity values for each and every element. The sensitivity matrix derived in this manner is, in this paper, called the uniform sensitivity matrix, denoted by $\mathbf{S}_{unif}$. However, the relationship between the conductivity changes and the corresponding differential boundary voltages is not linear and virtually no interrogated region is uniform. The current distribution and therefore the voltage distribution within a body depends on the conductivity distribution within the body and as a consequence this is also true of the sensitivity matrix. For example, a small change in conductivity next to a physically large conductive area will have a smaller effect on the boundary voltages than the same small change in conductivity next to a relatively small area. Thus the coefficients of the true sensitivity matrix vary with the conductivity distribution and this matrix is referred to in this paper as the ideal sensitivity matrix, $\mathbf{S}_{ideal}$. In general therefore, although the sensitivity matrix ***S*** changes with the conductivity distribution and equation (1) is therefore non-linear, it has been argued that for small changes in conductivity this non-linearity can be ignored (Barber and Brown, 1990). Shaw et al (1993) have also reported a similar result, namely that for a small region, the linear approximation is valid for the conductivity changes of up to 300% of the background.

We have determined that the assumption of linearity by Barber and Brown (1990) is violated in conditions where there is a wide range of conductivity values; this is in accordance with findings by Seagar (1983). Given accurate spatial and conductivity information about a region to be imaged, an accurate image of the impedance distribution can be reconstructed from the boundary voltage data. Although this may be self-evident, it shows whether or not the relationship described by equation (1) is valid. It also shows the extent of the blurring of the image due to the algorithm and computational process. Also, it serves as a benchmark for images obtained using less *a-priori* information and as such is the "best" image that can be obtained. Recognising that in general complete anatomical information will not be available, this paper will

address the degree of accuracy needed in the *a-priori* information in order to produce a useful reconstructed image. If the method is reasonably robust it may be possible to use anatomical information taken from a database rather than from the subject being imaged, contrary to previous speculations (Zadehkoochak et al (1993)). However it will be shown in the work presented in the paper that providing the model is closely matched to that of the interrogated area an improvement in image quality is achieved. It also will be demonstrated how the present widely used sensitivity algorithm can be combined with an approximate knowledge of the spatial distribution of the tissues to provide a better estimate of the conductivity values.

2. Method

In order to generate the sensitivity matrix **S** the area of interest, a 2D circular tank, is split into 1920 triangular and brick elements as shown in figure 1. The elements representing the modelled electrodes are not shown in the reconstructed images and the central elements are not displayed well due to their small size.

The sensitivity matrix **S** is a matrix of 208 by 1920 coefficients. The 208 rows of the **S** matrix relate to the 208 different differential voltage readings and the 1920 columns to the sensitivity coefficient for each independent element. There are 13 voltage measurements for each of the sixteen projections, giving 208 voltage readings. Each of the 1920 elements in the model has its conductivity value perturbed from a uniform value and this small change generates 208 differential boundary voltage changes. The sensitivity coefficient for each element i was calculated from Geselowitz's lead theory (Geselowitz 1971) and is given by:

$$S_{(j,i)} = -\int_u \nabla\Phi_m \cdot \nabla\Psi_n \cdot du \qquad (2)$$

where j = j(m,n), Φ_m is the potential distribution generated in an object when unit current is passed through the electrode pair m before a change in conductivity (σ_{ref}) and Ψ_n is the potential distribution produced if unit current had been injected through electrode pair n after the change in conductivity to σ_{dat} has occurred. j is the drive and receive electrode combination and the integration is over the area of the element u, i.e. multiplication of the dot product with the area of the element u.

The electric fields $\nabla\Phi$ and $\nabla\Psi$ are calculated for each element using an available finite element package. The two vector components of the electric field (Ex_i and Ey_i) are calculated at the centre of each element for every drive-electrode combination.

As Φ_m and Ψ_n are derived for different conductivity distributions equation (1) is non-linear in terms of conductivity. However, for small changes in conductivity about σ_{ref}, Ψ_n can be replaced by the equivalent potential calculated for σ_{ref} and this linearises the problem. For large changes the assumption of linearity is no longer correct: a problem this paper addresses.

The linearised sensitivity matrix $\mathbf{S_{unif}}$ is calculated assuming that the conductivity distribution is uniform before and after a change has occurred and this is the matrix which has been used to date even when the reference conductivity is not uniform (Barber and Brown 1990, Kotre 1989).

The sensitivity coefficient for each element of $\mathbf{S_{unif}}$ was calculated using equation (3), where for the electric field (Ex_m, Ey_m) in element i is due to the current injected through electrode pair m and the electric field (Ex_n, Ey_n) is that produced when the same current is injected through electrode pair n.

$$S_{unif_{(j,i)}} = -\int_u (Ex_m, Ey_m).(Ex_n, Ey_n)du \qquad (3)$$

The integration is again over the area of the element u.

In principle the calculated sensitivity matrix can now be used to reconstruct an image of the change in conductivity distribution calculated from the boundary potential differences. This relationship can be derived from equation (1) to give:

$$\Delta\sigma = S^{-1}\Delta v \qquad (4)$$

where $\mathbf{S^{-1}}$ is the inverse of **S**.

S is a non-square (208 x 1920) and ill-conditioned matrix. Using the damped least squares method (Menke 1989):

$$\Delta\sigma = [S^T S + \lambda F_{\max} \mathrm{I}]^{-1} S^T \Delta v \qquad (5)$$

where $\mathbf{S^T}$ is the transpose of **S**, λ is the regularisation factor, F_{max} is the maximum main diagonal element value of matrix $[S^T S]$ and I is a unity

diagonal matrix of same size as $[S^T S]$. The square matrix $[S^T S]$ is regularised in order to reduce the condition number for the system and hence obtain an approximate inverse and hence an approximate solution. For a non-zero value of λ an inverse can be calculated although its condition number, and hence the stability of the inversion, will depend on λ. Generally speaking if λ is large the reconstructed image will be too smooth and blurred but if λ is too small the image will be dominated by noise.

Figure 2 shows an example of the effect of varying λ on the (resultant) reconstructed image. In this case the sensitivity matrix is that calculated for uniform conductivity distribution, $\mathbf{S}_{\mathbf{unif}}$. The model used to generate the boundary voltage data is also shown in figure 2(a). The conductivity values used in the finite element model are shown in Table 1 (Weast R, 1989). These conductivity values are different but not significantly different compare with the values used by other workers but note that the underlying principle described here will apply to any tissue conductivity value. $\mathbf{S}_{\mathbf{unif}}$ was calculated by using a uniform conductivity distribution consisting of skeletal muscle tissue. λ is represented as fraction of the maximum diagonal value of matrix $[S^T S]$, where $F_{max} = 2.8653 \times 10^{-15}$. In general terms, as λ decreases, more singular values of matrix $[S^T S]$ are included in the calculation of the pseudo-inverse. It can be seen that this results in the image of the organs being pushed in towards the centre of the interrogated area and the image also contains more artefacts. For higher values of λ the image of the organs looks more spread out and blurred. These images are static images and are produced by adding the known reference conductivity (σ_{ref}) to the calculated change in conductivity $\Delta\sigma$.

Table 1. The conductivity values of biological tissue.

	Muscle	Lung	Heart
Conductivity (Sm^{-1})	0.74	0.11	1.16

We now replace the sensitivity matrix $\mathbf{S}_{\mathbf{unif}}$ with the correct sensitivity matrix $\mathbf{S}_{\mathbf{ideal}}$. The calculation of the sensitivity coefficient for each element of $\mathbf{S}_{\mathbf{ideal}}$ is done by modifying equation (3) to include the change of conductivity to give:

$$S_{ideal(j,i)} = -\int_u (Ex_m, Ey_m).(E'x_n, E'y_n)du \qquad (6)$$

where for element i the electrical field components (Ex_m, Ey_m) in element i are due to the current injected through electrode pair m for the uniform conductivity and the electrical field components ($E'x_n$, $E'y_n$) produced when the same current had been injected through electrode pair n after there has been a change in conductivity from σ_{ref} to σ_{dat}, for pixel i, where σ_{ref} is the uniform conductivity, i.e. 0.74 Sm^{-1}, and σ_{dat} is the actual conductivity of pixel i for the thorax model used.

Figure 3(a) shows four two-dimensional models of the human thorax used for the calculation of the corresponding four electric field distributions and the four resulting differential boundary voltage profiles. Figure 3(b) shows the resulting reconstructed images using the calculated boundary voltages and the corresponding $\mathbf{S}_{\mathbf{ideal}}$ for each of the thorax models with λ set at 0.01 for the calculation of each pseudo-inverse. F_{max} for a typical ideal sensitivity matrix is 5.9324×10^{-15}. The conductivity values used are again as shown in Table 1.

The sensitivity matrix $\mathbf{S}_{\mathbf{ideal}}$ for each of the four models has a rank of 208 and is better conditioned than the corresponding square matrix formed from $\mathbf{S}_{\mathbf{unif}}$, a result which has not been commented on before.

The rank of 208 for a sensitivity matrix calculated from two non-equal electric field is not surprising as the reciprocity in this ideal sensitivity matrix will no longer be valid. But reciprocity in the differential boundary voltage data still holds and therefore the maximum possible rank of the data set will be104 and therefore the overall underlying problem of reconstruction will have only a rank of 104.

Figure 4 shows a plot of the singular values of two square matrices $[S^T S]$, calculated using $\mathbf{S}_{\mathbf{unif}}$ and $\mathbf{S}_{\mathbf{ideal}}$. Initially, the differences between the singular values of the two different matrices are small. After the first 30 values the singular values from the square matrix $[S^T S]$ formed using $\mathbf{S}_{\mathbf{unif}}$ decay more rapidly than those of the square matrix $[S^T S]$ formed using $\mathbf{S}_{\mathbf{ideal}}$. This means that larger singular values are used in image reconstruction when using $\mathbf{S}_{\mathbf{ideal}}$ resulting in a better reconstructed image. The reconstructed image of the modelled ideal human model obtained using $\mathbf{S}_{\mathbf{ideal}}$, figure 3(b)i, is more accurate than the corresponding image obtained using $\mathbf{S}_{\mathbf{unif}}$, figure 2, because $\mathbf{S}_{\mathbf{ideal}}$ incorporates the correct full anatomical and conductivity information. However, in clinical practice, the information used in the calculation of $\mathbf{S}_{\mathbf{ideal}}$ is not available.

In a clinical case where no information about the internal conductivity distribution is available it may be possible to estimate the conductivity distribution. For example, if an anatomical image from another high resolution modality, such as MRI, were available it should be possible to use this data, plus published values of tissue conductivity, to construct an initial $\mathbf{S}_{\mathbf{ideal}}$ which should certainly be an improvement on $\mathbf{S}_{\mathbf{unif}}$. However, a more economical approach might be to use an MR image taken from a data base of images. In this case the image would not be a perfect match to the patients' anatomy but could be sufficiently close to provide a useful $\mathbf{S}_{\mathbf{ideal}}$. To test this approach, a total of six different *a-priori* models, figure 5, were constructed, whose spatial conductivity distributions were varied from an over-estimation to an under-estimation of the patient model of figure 2(a), the ideal model. The conductivity values for the regions within the six models were calculated by superimposing each model onto the ideal patient model and averaging the conductivity values of each element within the area covered by each non-ideal patient region. The total conductivity of each model is kept constant and equal both to each other and to the ideal model. This method of calculating the conductivity values was chosen rather than using a typical set of published values to allow for a wider range of possible conductivity values. The model is not restricted to a fixed geometry and also the regional conductivity values are allowed to vary within a considerable range. The conductivity values used for each model are shown in Table 2.

Table 2. The conductivity values used for the non-ideal patient models shown in figure 5.

	Muscle (Sm^{-1})	Lung (Sm^{-1})	Heart (Sm^{-1})
Model (a)	-	0.07	0.64
Model (b)	1.5	0.08	0.8
Model (c)	0.75	0.11	1.06
Model (d)	0.5	0.17	1.6
Model (e)	0.38	0.33	3.19
Model (f)	0.3	-	-

These models were used as the *a-priori* information and a new ideal sensitivity matrix was calculated for each of the six different *a-priori* models using the same method as described for the previous example. Two regularisation factors, λ of 0.1 and 0.01, were chosen for image reconstruction for each case. These values have been selected a *posteriori* by

visual examination. The regularisation parameter could also be chosen by some objective method (for example the L-curve method or the Morozov discrepancy principle) but these do not always give (visually) meaningful results (Kolehmainen et al 1997). Also, in practice, where there is more noise than usual in the data, a high value such as 0.1 must be used to minimise the reconstruction error by damping out the noise with a consequent loss in spatial resolution. This is visually evident from the reconstructed images shown in Figure 2.

The boundary voltage data taken from the ideal patient model was used to reconstruct a set of images using each of these six new ideal sensitivity matrices for each of the two values of λ ; figure 6(b) (λ = 0.1) and figure 6(c) (λ = 0.01). As a measure of the accuracy of the new reconstructed images, the Δ rms, on a pixel by pixel basis, was calculated with respect to the ideal reconstructed image of the same value of λ , as shown in figure 6(a)(ii-iii). The Δ rms values for the six images in figure 6 are shown in Table 3. The Δ rms is given by:

$$\Delta rms = \sum_{i=1}^{1920} \left(u \times \sqrt{\frac{(\sigma(i)_{calculated} - \sigma(i)_{ideal})^2}{2}} \right) \qquad (7)$$

where $\sigma(i)_{calculated}$ is the calculated conductivity for a pixel, $\sigma(i)_{ideal}$ is the 'ideal' or best reconstructed conductivity for the same pixel and u is the area of the pixel.

Table 3. The Δ rms of the new reconstructed images shown in figure 6(b and c) with respect to the ideal reconstructed image, figure 6(a)i-ii.

	Δ rms (λ =0.1)	Δ rms (λ =0.01)
Model (a)	1.36×10^{-6}	2.06×10^{-6}
Model (b)	9.97×10^{-7}	1.56×10^{-6}
Model (c)	6.40×10^{-7}	9.03×10^{-7}
Model (d)	1.15×10^{-6}	1.70×10^{-6}
Model (e)	1.42×10^{-6}	2.52×10^{-6}
Model (f)	1.30×10^{-6}	3.34×10^{-6}

The smallest value of the Δ rms is seen when model (c) is used for the *a-priori* information, where this *a-priori* model matches the actual model well with respect to both geometrical and conductivity information. When *a-priori*

model (b) is used the reconstructed image gives the second best results. Since this model has a geometry similar to the actual model, but a different conductivity, this highlights the importance of correctly chosing a suitable *a-priori* model of anatomical information. The Δ rms increases as the differences between the *a-priori* model and the patient model increases; it is worth noting that the value of λ =0.1 reconstructs the more accurate image.

These models all contain some estimates of the conductivity values of the tissues. In practice these may not be known with any accuracy; indeed, the determination of the conductivity values is an important aim of EIT imaging. It has been shown that using a close approximation of the internal conductivity distribution improves the quality of the reconstructed images. It will be now shown how the anatomical information can be used, without making any prior assumptions about tissue conductivity values, in order to determine these conductivities.

Initially, all the conductivity values are assumed the same. The boundary voltage data from the ideal patient model is used together with the uniform sensitivity matrix $\mathbf{S}_{\mathbf{unif}}$ to reconstruct an initial image of the internal conductivity distribution for the ideal patient. The ideal structural information as shown in figure 7(a)i was super-imposed over the reconstructed image figure 7(b)i for (λ = 0.1) and figure 7(c)i for (λ = 0.01), and the reconstructed conductivity values of the initial image in each segment of the superimposed image were averaged. These conductivity values were used to calculate a new electric field distribution and hence a new sensitivity matrix which was then used to produce another new reconstructed image. This step was repeated until no further improvement to the reconstructed images was found; in this case after 9 iterations. Two regularisation factors λ =0.1, figure 7(b), and λ =0.01, figure 7(c), were used. To measure the accuracy, the ideal image was reconstructed for each value of λ , figure 7(a)ii and (a)iii, and Δ rms was calculated for each image with respect to its ideal image reconstructed with the same value of λ . The reconstructed images at iteration step 9 of both values of λ are shown in figure 7(b)ii and figure 7(c)ii.

If the sensitivity matrix is not correct it is possible, due to high non-linearity of the problem, for negative conductivity values to be calculated from boundary voltage data - a physical impossibility. Where this occurred the conductivity was set to the small value of 0.01 Sm^{-1}. The conductivity values for each region calculated at iteration steps 1 and 9 are shown in Table 4.

Table 4. The conductivity values for each region of images found in figure 7b and 7c

	Muscle (Sm^{-1})	Right lung (Sm^{-1})	Left lung (Sm^{-1})	Heart (Sm^{-1})
λ =0.1: Iteration step 1	0.67	-0.04	-0.01	0.62
λ =0.1: Iteration step 9	0.69	0.26	0.27	0.69
λ =0.01: Iteration step 1	0.55	-0.78	-0.71	0.73
λ =0.01: Iteration step 9	0.71	0.48	0.47	0.79

Figure 8 shows the plot of the Δ rms calculated for each of the two regularisation factors at each step of the iteration process.

It can be seen that after the 1st iteration the Δ rms is reduced and in spite of the oscillatory behaviour some further improvement in the image quality measure seems possible although the image does not converge exactly to the ideal image. It can be seen that due to non-linearity the calculated conductivity values, shown in Table 4, the values at iteration step 1 are inaccurate, and in some cases negative; by iteration step 9, although the calculated conductivity values do not accurately match the actual values, they are no longer negative and are closer to their actual value.

The aim of the next set of experiments was to investigate how close the estimated anatomical structure must be to the actual patient anatomy model for a successful iteration, i.e. an improved reconstructed image. In this part of the study boundary data was calculated from three various patient models using the models shown in figure 9(a)i-iii. These data sets were used together with a pre-defined set of internal conductivity distribution, figure 9(b), in the iterative method already described. In this case we simulate the situation where the *a-priori* model for the anatomy was the same for all modelled patients. The reconstructed images using the uniform sensitivity matrix are shown in figure 9(c)i, figure 9(d)i and figure 9(e)i for each patient model data shown in figure 9(a)i-iii respectively. The reconstructed images at iteration step 9 is shown in figure 9(c-e)ii. The regularisation factor of λ =0.1 was used for all cases. The conductivity values for each region calculated at iteration steps 1 and 9 are shown in Table 5.

Table 5. The conductivity values for each region of images found in figure 9(c) - 9(e)

	Muscle (Sm^{-1})	Right lung (Sm^{-1})	Left lung (Sm^{-1})	Heart (Sm^{-1})
Image 9c: Iteration step 1	0.35	-0.51	-0.48	0.70
Image 9c: Iteration step 9	0.58	0.50	0.49	0.77
Image 9d: Iteration step 1	0.66	-0.05	-0.03	0.60
Image 9d: Iteration step 9	0.68	0.27	0.27	0.68
Image 9e: Iteration step 1	0.75	0.26	0.27	0.61
Image 9e: Iteration step 9	0.75	0.34	0.35	0.65

Figure 10 shows the plot of the Δ rms calculated for each of the images in figure 9(c-e) with respect to their ideal image reconstructed at the same value of λ =0.1.

It can be seen that once again after the 1st iteration the Δ rms is reduced and again although the behaviour is oscillatory some further improvement seems possible. The best improvement is seen in the images reconstructed when the patient data comes from a model which closely approximates the *a-priori* model used for the iteration. It can be seen from the calculated conductivity values that due to the non-linear nature of the problem, negative conductivities were calculated at iteration step 1. By step 9, however, using the technique for handling negative calculated conductivity values previously described, the final conductivity values were generally closer to the actual conductivities. The image in Figure 9(d)ii is the closest to its ideal reconstructed image, demonstrating that the use of *a-priori* anatomical information close to the true anatomical information produces better calculated conductivity values.

3. Discussion

Three cases have been presented where the inclusion of anatomical *a-priori* information into the reconstruction algorithm has been tested. In the first case, a complete set of *a-priori* information was used. This included not only the internal conductivity distribution (geometrical positions of organs) but also the true conductivity values of each region. The resulting reconstructed image showed a great improvement in comparison with an image reconstructed where no *a-priori* information had been included. This shows as expected that given all the *a-priori* information a much more accurate image can be reconstructed from the boundary data. Of course, if such information were available no imaging would be required but this work does show the best usable image possible. In the second case, an *a-priori* approximation was made to the internal anatomy (six approximate cases, from over-estimation to under-estimation), together with an estimate of the conductivity values for the interrogated area. The results show an improvement in the (resulting) reconstructed image compared to the images obtained using only the standard sensitivity matrix $\mathbf{S}_{\mathbf{unif}}$. The best improvement is seen when the approximation to the internal structure is a close match to the actual anatomy.

This work has shown that a high value of regularisation factor works well compared to smaller values where computational noise is present. Also, it has been shown that it is possible to iterate from the initial reconstructed image to a more accurate image using a sensitivity matrix which has been calculated initially from a uniform conductivity distribution together with the anatomy of the region to be imaged. Using this method, improvements are seen after the first iteration. No visible improvements were found after the ninth iteration. Finally, the boundary data from three patient models have been used to reconstruct images using a sensitivity matrix which was initially calculated from a uniform conductivity distribution. Using a model of the estimated anatomy, it has been found that there is an improvement in the reconstructed images using the iterative method proposed here. The best improvement were seen when the *a-priori* anatomy closely matched the modelled patient's anatomy. Traces of the anatomical model used to estimate the *a-priori* information can be clearly seen in all the final images reconstructed using this iterative method. These images may not be visually more accurate but the calculated conductivity values are more accurate than those where the reconstructed images are obtained as a single pass from the uniform sensitivity matrix.

Future work on this image reconstruction method could include the ability to adjust the shape of the anatomical information, within appropriate constraints, to more closely represent the anatomy of the patient. This could be done by defining an appropriate warping function whose parameters are treated as unknowns in the reconstruction process. To further investigate the accuracy of the *a-priori* information needed, the effects due to rotational mismatch of the anatomical information used can also be studied. Chest expansion has been shown to create an additional artefact in EIT measurements of the thorax (Alder et al 1994). Further considerations may be needed to include more accurate *a-priori* information where any chest expansion is considered.

4 .Conclusion

A considerable improvement in the reconstructed image can be obtained by using accurate *a-priori* information about a region to be imaged. It has also been shown that a close approximation of such *a-priori* information also produces an improved reconstructed image. Finally, it has been demonstrated that given the present widely used sensitivity matrix which is calculated from a uniform conductivity distribution, together with a good approximation of the internal anatomy, it is possible to reconstruct a much improved image of the internal conductivity distribution using an iterative method. This improved image is more accurate in a quantitative manner, where the calculated conductivity values are nearer to the actual tissue conductivity values.

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