Reconstruction algorithm based on hard priors for EIT imaging of the prostate

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Abstract

In the current clinical setting, prostate biopsies entail sampling tissues at template-based locations that are not patient specific. In Wan et al 2010, we proposed a novel Ultrasound (US) coupled Transrectal Electrical Impedance Tomography (TREIT) system which features an endorectal US probe retrofitted with electrodes and demarcates suspect tumor regions based on their electrical properties; the aim of the system is to guide prostate biopsies. TREIT imaging of the prostate is a severely ill-posed problem as it estimates parameters in an open domain. Furthermore, as the conductivity contrast between the prostate and its surrounding tissue is much larger than the difference in conductivities between benign and malignant tissues in the prostate, reconstructing contrasts within the prostate volume is challenging. To help overcome this problem, hard priors can be implemented so that parameters are estimated only within the prostate volume; however, this requires the availability of structural information. We introduce a method that allows us to use the US images to delineate the prostate surface and to incorporate this information into the reconstruction. In this paper, we evaluate the performance of this algorithm against an algorithm which does not use structural information, in the context of numerical simulations and phantom experiments. We show that the proposed algorithm is able to identify contrasts within the prostate volume while the algorithm that does not use structural information is not able to localize these contrasts. As our sensitivity decays rapidly with distance from the probe, the size of contrasts localized in numerical simulations was smaller than the actual inclusion; however, our aim is to use the system to guide prostate biopsies so knowledge of the general vicinity of cancerous tissue is useful information as it allows finer sampling in suspicious areas.

1. Introduction

In a paper published in 2010, we presented a novel Ultrasound (US) coupled Transrectal Electrical Impedance Tomography (TREIT) system for Prostate Imaging (Wan et al 2010). In the current clinical practice, prostate biopsies entail sampling tissues at set locations that are not patient specific. The aim of the TREIT system is to guide prostate biopsies so additional tissue core samples can be taken from suspicious regions as demarcated by the reconstructed Electrical Impedance Tomography (EIT) images. In this paper, we present further results relative to incorporating US structural information in our reconstruction algorithm to enhance reconstructions for prostate imaging. EIT is an imaging technique that is used to reconstruct electrical conductivity and permittivity in a volume. The technique is based
on surface electrode measurements. A set of electrodes are applied to the skin, a pair of electrodes injects and sinks an alternating current in the volume to be imaged, and the resulting potentials are measured at pairs of sensing electrodes; this procedure is repeated for different injection and sensing pairs. Using these measurements, conductivity and permittivity images can be reconstructed. Cancerous tissue in the prostate presents lower conductivity than benign glandular or stroma tissue (Halter et al 2009); therefore, lower conductivities in EIT images indicate tumorous regions.

In the system we developed, electrodes are retrofitted to a commercial, endorectal US probe. In this application, we image a volume in front of the electrode array. This open-domain geometry makes TREIT particularly challenging as the current density and, consequentially, sensitivity decreases rapidly with distance from the probe, worsening the posedness of the already ill-posed EIT problem (Borsic et al 2010). The specific application of TREIT to prostate imaging has the added difficulty that the conductivity of the prostate is much higher than its surrounding tissue (Gabriel et al 1996) which makes it harder to discern contrasts within the prostate volume. The prostate is itself a large contrast and we are interested in identifying contrasts within this contrast.

One way to improve images is to incorporate structural information in the reconstruction (Borsic et al 2010, Borsic et al 2002 and Vauhkonen et al 1996). We propose to use US images to delineate the boundaries of the prostate and to estimate electrical properties only within the segmented volume. We introduce a method that allows embedding of the volume, as identified from US images, into a mesh that is used for image reconstruction. The performance of the algorithm is evaluated on simulated data and phantom experiments. The resulting images are compared against reconstructions produced with an algorithm introduced in Borsic et al (2010), which does not use a priori information in the reconstruction. The proposed implementation successfully isolates contrasts within the prostate while the algorithm that does not use prior information is unable to identify these contrasts.

In section 2, we detail the segmentation and meshing procedures used. Section 3 describes the reconstruction algorithm proposed in this paper. Section 4 and Section 5 present and compare results of the reconstruction algorithms on numerical simulations and phantom experiments, respectively.

2. Incorporating Structural Information

In this section, we discuss why using structural information in the reconstruction is particularly useful for TREIT imaging of the prostate, we describe different ways in which this information can be incorporated, and explain how this information is obtained and used in the proposed implementation.

2.1 Information available from the US

Using TREIT to image the prostate is a particularly challenging problem as the conductivity contrast between the prostate and the surrounding periprostatic adipose-rich tissue is approximately 5, which is higher than the conductivity difference between normal and benign tissue within the prostate which is around 1.3 (Gabriel et al 1996). Therefore, changes in the measured voltages at the electrodes are dominated by the conductivity difference between the prostate and its background which makes it difficult to identify contrasts within the prostate volume. Furthermore, the EIT data is acquired in an
open-domain, which is the region in front of the electrodes; this makes the TREIT problem severely ill-posed as the imaging sensitivity decays rapidly with distance from the electrodes.

When prior information is available, it can be incorporated into reconstruction algorithms as hard or soft priors to improve EIT images. Soft priors, for example, can be used to favor changes in preferred directions and are generally implemented in the regularization functional (Borsic et al 2002 and Kaipio et al 1999). Borsic uses anisotropic regularization filters to relax constraints in the direction normal to the discontinuity of interest, such as inter-organ boundaries. The regularization functional is built in such a way that it favors a certain direction more than the others in the part of the domain where prior information is available, while maintaining uniform regularization weights for the background. Another technique, namely subspace regularization, develops the regularization functional so that its null space contains the true solution (Vauhkonen et al 1996). Therefore, the regularization draws the solution towards the prior. In Vauhkonen et al (1996), the solution space is developed using a priori information about the anatomy of the volume to be imaged as well as the resistivities of its constituent tissues. An example of reconstruction based on hard priors is the basis constraint method which reconstructs a conductivity image as a linear combination of a set of basis images, where the basis images are an ensemble of conductivity models (Vauhkonen et al 1997). Borsic et al (2010) presents an algorithm which reconstructs conductivities in a wedge-shaped sub-volume of the imaging domain, which includes the prostate. In this formulation, by grouping neighboring elements into regions of interest (ROI) within a volume encompassing the prostate and reconstructing a single value of conductivity on each ROI, the resolution of the reconstruction can be controlled; let’s refer to this algorithm as “subvolume reconstruction”. This approach does not overcome the problem of identifying contrasts in the prostate which present lower conductivity contrast than the difference in conductivities between the prostate and its surrounding tissue.

Although hard priors perform better, they require structural information to be available; therefore, soft priors are generally used in EIT. As we have accurate structural information from the US images, we implement hard priors using a variation of the subvolume reconstruction algorithm where we reconstruct conductivities only within the prostate volume instead of on a subvolume of the imaging domain. Ultrasound is insensitive to cancer so it can only be used to provide anatomic information about the prostate; we propose to use the US images to delineate the prostate boundaries. By estimating parameters on ROIs in the segmented prostate volume while assuming a single-value of conductivity for the surrounding region, we expect to see an improvement in the reconstructed images. Our goal is to overlay the EIT images on the US segmentations for guiding the biopsy sampling in regions where tumors may be present.

2.2 Combined US and TREIT system

We developed a combined US and TREIT system which features a clinical, 3D transrectal US probe to which a flex circuit of 30 electrodes is attached, as illustrated in Figure 1. The electrodes lie on the periphery of the acoustic window of the probe and are rigidly placed so that there is a 140° aperture through which ultrasound signals can image the prostate; a complete description of the system can be found in Wan et al 2010 and Borsic et al 2010. The placement of the electrode array over the acoustic
window allows for co-registration of the ultrasound images with the EIT data, as the electrodes are seen as reflections in the US images. The probe is mounted on a rigid, articulated arm, as shown in Figure 2, which is used to position and lock the probe into place to ensure accurate positioning during data acquisition.

In a typical acquisition with the TREIT system, 61 transverse US images are collected at 1mm steps and EIT data is acquired using the electrode array.

![US Acoustic Window and Electrodes](image)

**Figure 1** – TRUS probe with retrofitted TREIT System

![Combined TRUS/TREIT system](image)

**Figure 2** – Combined TRUS/TREIT system mounted on an articulated, rigid arm

### 2.3 Outlining US images

We are currently using the TREIT system, in the Operating Room (OR), to run clinical trials on patients that are undergoing radical prostatectomies. This gives us access to excised prostates and their histopathological data which can be used to verify reconstructed impedance images. At present, data is reconstructed offline. In the future, we aim to use the system to guide biopsies; therefore, image reconstruction, which includes segmentation of the US images of the prostate, needs to be performed in real-time in the OR. To this effect, we have implemented custom segmentation software on a touch-screen monitor, which allows the surgeons to outline the prostate boundaries on US images using their
finger; a chain of software uses the segmentations to automatically generate a volume mesh with the embedded prostate to be used for the reconstruction.

Visualization and segmentation tools were developed using Visualization ToolKit (VTK) functions and a GUI was implemented to control the segmentation software. Specifically, the vtkContourWidget was used to allow the users to draw contours on the US images by trailing their finger across the boundary of the prostate. As the user contours the images, a pixilated outline represented by Bézier curves appears in real-time as illustrated in Figure 3 (b).


2.4 Segmented Masks

Once all the slices have been segmented, MATLAB is used to generate region-of-interest (ROI) masks from the contours, as shown in Figure 4 (a). After masks have been generated for all the segmented slices, they are fed into a surface mesh generator which will generate a surface representation that will be changed into a volume mesh and used for the reconstruction.

![Figure 3](image1.png)

**Figure 3** – Example 2D US slice of an agar phantom (a) before and (b) after segmentation

![Figure 4](image2.png)

**Figure 4** – (a) Binary mask generated from a segmented 2D contour (b) Surface mesh generated using the Marching Cubes algorithm (c) Smoothed version of surface mesh shown in Fig 4(b)
2.3 Prostate Surface Mesh Generation

From the 2D masks, we generate a surface mesh using a Marching Cubes (MC) algorithm (Wu and Sullivan 2003). An example surface mesh generated using the MC is shown in Figure 4 (b). Although a higher number of elements model the prostate more closely to the original segmentation, this increases computation time for the reconstruction. The surface mesh is smoothed to produce a mesh with 2200-2800 elements using the vtkSmoothPolyDataFilter filter; as an example, Figure 4 (c) shows the smoothed version of the surface mesh in Figure 4 (b). The chosen range for the number of elements represents a compromise between preserving the general shape of the prostate and maintaining low computation time for the reconstruction algorithm. Further, using a finer mesh does not necessitate a more accurate representation of the actual prostate as we are limited by the accuracy of the segmentations, which have shown variations between users.

2.6 Volume Mesh Generation

Given a surface representation of the prostate, we want to embed it into a volume which will be used for image reconstruction. The volume mesh must also include the electrodes so the flow of currents can be properly modeled. As the geometry of the imaging probe is fixed, we have on file a surface mesh that represents the probe, the electrodes and a volume around it as illustrated in Figure 5 (a). The cylinder in this mesh represents the volume being imaged and the diameter of the cylinder is set to be large enough that the applied imaging field at the electrodes decays to $1 \times 10^{-4}$ of its original value at the periphery of the cylinder, as determined empirically (Borsic et al 2010). In this FEM mesh, we embed the surface mesh of the prostate, as illustrated in Figure 5 (b), and generate a volume mesh of the consolidated surface mesh using an open-source software called Tetgen (TetGen).

![Figure 5](image.png)

**Figure 5** – (a) FEM mesh of US probe and electrode array embedded inside a 24cm cylinder. (b) FEM mesh with an embedded phantom surface mesh

This process allows us to produce a volume mesh with a subvolume that represents the prostate and allows estimation of imaging parameters within that subvolume.
3. Reconstruction Using Hard Priors

The forward problem in EIT involves solving Laplace’s equation in the region of interest; in our case, this would be the prostate volume and a region around it.

\[ \nabla \cdot \sigma \nabla u = 0 \]  

(1)

where \( \sigma \) is the conductivity or admittivity distribution in the region of interest and \( u \) represents the electric potentials in the body.

Equation (1) is solved using the boundary conditions known as the Complete Electrode Model (Somersalo et al. 1992) which accounts for the electrode contact impedances and this allows for the electric potentials within the imaging domain to be determined.

A standard Tikhonov-regularized, nonlinear least-squares reconstruction algorithm is used to reconstruct the data. The reconstructed conductivities are given by:

\[
\sigma_{\text{rec}} = \text{argmin}_\sigma \frac{1}{2} \| V(\sigma) - V_{\text{meas}} \|^2 + \alpha \frac{1}{2} \| L(\sigma - \sigma^*) \|^2. 
\]  

(2)

where \( \sigma \) is the vector of conductivities to be estimated, \( V(\sigma) \) are the simulated voltages at the surface electrodes obtained from the forward solver, \( V_{\text{meas}} \) is the set of measured potentials at the electrodes, \( \alpha \) is the Tikhonov factor, \( L \) is a regularization matrix, which is a discretised Laplacian in our implementation, and \( \sigma^* \) is a reference conductivity distribution. EIT is a severely ill-posed problem which means that small errors in the measurement can lead to instability in the solution. In the presence of noise, the Tikhonov regularization term, \( \frac{1}{2} \| L(\sigma - \sigma^*) \|^2 \), ensures stability of the solution. Iteratively solving (2) using the Newton-Raphson method gives the conductivity update formula:

\[
\delta \sigma_n = - \left( \frac{1}{2} J_n^T L_n \frac{1}{2} J_n + \alpha L_n \right)^{-1} \left[ J_n^T (V(\sigma_n) - V_{\text{meas}}) - \alpha L_n (\sigma_n - \sigma^*) \right], 
\]  

(3)

where \( \delta \sigma_n \) is the conductivity update for iteration \( n \) and \( J_n \) is the Jacobian of the forward operator \( V(\sigma) \) calculated for \( \sigma = \sigma_n \). Given the nonlinearity of the problem, a parabolic line search procedure is used (Nocedal et al. 1999).

\[
\sigma_{n+1} = \sigma_n - \beta \delta \sigma_n, 
\]  

(4)

where \( \beta \) is a scalar value determined by the line search process. Equations (3) and (4) are iterated three times to minimize the objective function in (2). For noisy data, it was empirically found that iterating more than three times typically results in conductivity changes of less than 5% in the norm of the reconstructed conductivities for further iterations (Borsic et al. 2010).

To exploit the prior information, we intend to reconstruct conductivities in the prostate volume while estimating a single value of conductivity for the region outside the prostate. Since sensitivity decreases with distance from the probe, the problem is particularly ill-posed; reconstructing conductivities on a small number of large ROIs within the prostate improves the posedness of the problem as well as reconstructions (Wan et al. 2010). The FEM mesh presented earlier is a fine mesh with 97 973 nodes and 541 604 tetrahedral elements (Borsic et al. 2010). Using this mesh for the forward problem ensures high accuracy; however, the reconstruction must be computed on a coarser representation of the mesh. We
want to estimate conductivities in the prostate volume while maintaining a homogeneous conductivity for the background. As the estimated conductivity profile from the forward solver is used to start the reconstructor, the coarse representation of conductivity must be constructed in a way that establishes a direct relation between the fine mesh and ROIs used for the reconstruction. To setup this relation, we start by generating a number of points, known as ‘seed points’, inside the prostate volume, as illustrated in Figure 6 (a). Elements in the fine mesh that are close to the seed points are grouped together to form volumes that are used as ‘coarse voxels’, as shown in Figure 6 (b), on which parameters of the reconstruction are estimated. Grouping fine elements based on proximity to the seed points leads to a direct and linear correspondence between the fine and coarse representation of the mesh. In this formulation, the number and locations of the seed points directly controls the number, size and location of coarse pixels. By setting up relatively large voxels in the prostate volume, we can improve our imaging sensitivity in the prostate.

In the next two sections, we present reconstructions based on numerical experiments and phantom studies. For the reconstructions shown in these sections, we used a set of 500 optimized tetrapolar measurements with an additional 2000 measured patterns where sensing and excitation electrode pairs were chosen randomly as we found these to improve reconstructions. Optimality here refers to using linearly independent patterns that maximize sensitivity to conductivity changes in the imaging volume or ROI (Borsic et al 2010). Borsic et al presents a more comprehensive treatment of how the optimal patterns are chosen in Borsic et al (2010).

4. Numerical Experiments

In this section, we use synthetic data to compare the performance of the proposed reconstruction algorithm which uses prior information against the subvolume reconstruction algorithm, which does not use structural information. The subvolume reconstruction algorithm uses a reconstruction domain which encompasses the prostate. It works by generating a number of seed points in a wedge-shaped
subvolume of the imaging domain, as shown in Figure 7, and by clustering elements into coarse voxels for parameter estimation, based on proximity to these seed points, as visualized in Figure 8.

**Figure 7** – Visualization of the ‘seed points’, which are shown as yellow dots, inside the prostate volume, shown in red. In this figure, only the nodes of the fine mesh used for forward modeling are shown. (a) Side view of the ‘seed points’ in the prostate volume (b) Top view of the ‘seed points’ in the prostate volume

**Figure 8** – Visualization of the coarse conductivity grid inside the prostate mesh used for image reconstruction. The grid is formed by grouping neighboring elements on the underlying fine mesh into “coarse pixels” based on their proximity to the
‘seed points’. Colors were randomly assigned to the pixels in these images to aid visualization. (a) Side view of ‘coarse pixels’ in the prostate mesh (b) Top view of ‘coarse pixels’ in the prostate mesh

In order to produce data for the numerical simulation, we simulated a prostate surface mesh and generated synthetic data used for testing the reconstruction algorithms. A 2 cm spherical inclusion of conductivity 0.0625 Sm$^{-1}$ is simulated inside the prostate volume of conductivity 0.25 Sm$^{-1}$, with a homogeneous background conductivity of 0.1 Sm$^{-1}$. The contrast and the prostate are visualized in the first column of Figure 9.

![Figure 9](image)

**Figure 9** – A 2cm spherical inclusion of conductivity 0.0625 Sm$^{-1}$ was generated inside a phantom of conductivity 0.25 Sm$^{-1}$ with a homogeneous background conductivity of 0.1 Sm$^{-1}$. The synthetic data was used to evaluate the performance of the reconstruction with and without structural information in the presence of 0.1% additive noise. The first row of this figure shows vertical cross-sections of the images and the second row shows horizontal cross-sections, in each case. The first column is a visual representation of synthetic data to be reconstructed where the white region is the contrast we are interested in reconstructing and the red region simulates the prostate. The second column shows difference reconstructions of the synthetic data using structural information and the third column presents difference reconstructions of the synthetic data without the use of prior information.

Simulated measurements were produced from the synthetic data and 0.1% standard normal noise was added to the voltages obtained from the forward solver to simulate actual experimental conditions. The data with additive noise was then reconstructed with the two algorithms in question using difference reconstructions against a uniform background, where the phantom and inclusion were not present.

Difference reconstructions using *a priori* information correctly identify the contrast, as illustrated by the images presented in the second column of Figure 9, which show correct localization of the inclusion. Accurately determining the position of a contrast in EIT is difficult as the conductivity profile in a volume
is estimated based on boundary measurements. This problem is worsened in our case as the electrodes are used to image in an open domain and sensitivity decreases as we move away from the probe. In the reconstructed images, it is notable that the values near the far end of the prostate are harder to estimate, which stems from our reduced sensitivity in this region. Furthermore, the recovered contrast is smaller in size than the actual inclusion; this is also a direct consequence of the decaying sensitivity with distance from the probe. The diameter of the reconstructed inclusion was estimated as the Full Width at Half Maximum (FWHM) of the conductivity profile of a single row of pixels from the left wall of the prostate to the right wall, as illustrated in Figure 10; the diameter was found to be 0.95 cm which represents a relative error of 52.5% from the true value. By averaging conductivity values inside the reconstructed contrast and the prostate volume, the conductivity contrast between the inclusion and the prostate volume was found to be 44% compared to the actual difference of 25%. The reduction in size and contrast of the reconstructed inclusion is caused by the decaying sensitivity with distance from the probe surface.

Figure 10 – The graph shows the reconstructed conductivities along a horizontal row of pixels for the vertical cross-section shown in Figure 9. The diameter of the reconstructed contrast was estimated as the Full Width at Half Maximum (FWHM) of this conductivity profile.

Difference reconstructions performed on a sub-volume of the mesh without the use of a priori information were not able to identify contrasts within the prostate. The dimensions of the imaging sub-volume are selected by the user; in our reconstructions, we restrict the sub-volume to be 6 cm from the surface of the probe as the sensitivity decays too much at larger distances (Borsic et al 2010). The sub-volume spans 140° in the horizontal plane extending 70° in each direction from the center of the probe.
Inside the imaging volume, a coarse grid of pixels is generated with 10 pixels along the radial direction, 14 pixels along the angular direction and 14 pixels along the vertical direction, as visualized in Figure 6 (Borsic et al 2010). The vertical and horizontal cross-sections of the difference reconstructions are shown in the third column of Figure 9. It is clear that the prostate was recovered in the images but there are no discernable contrasts seen within the prostate volume.

5. Phantom Experiments

The method outlined in Sections 2 and 3, which uses structural information for reconstruction, were applied to a phantom experiment to evaluate the performance of the proposed algorithm. An egg-shaped, agar phantom with a plastic inclusion centered in the phantom, shown in Figure 12 (a), was suspended about 3 mm from the surface probe using thin nylon wire, and imaged using the TREIT system, as illustrated in Figure 11. The phantom had a conductivity of 0.25 Sm$^{-1}$; a plastic cube of dimensions 2cm x 2cm x 1.3 cm was used as the inclusion and centered along the vertical axis. The experiment was conducted in a cylindrical tank filled with saline solution of conductivity 0.1 Sm$^{-1}$, which is 2.5 times lower than the conductivity of the phantom.

![Figure 11](image_url) – Agar phantom of conductivity 0.25 Sm$^{-1}$ with a plastic inclusion of dimensions 2cmx2cmx1.3cm centered along its vertical axis was suspended 3mm from the surface of the probe; the TREIT system was used to collect EIT and US data. Figure 12 and 13 show difference reconstructions of this experimental data.

US and EIT data were acquired on the phantom and the US images were segmented and a volume mesh for the reconstruction was generated. Difference reconstructions were produced using the proposed algorithm and the subvolume reconstruction algorithm. In the TREIT system, the measured voltages are very small so absolute reconstructions are not expected to accurately identify the contrast.
The proposed algorithm successfully localized the contrast in the prostate volume though some artifacts exist. The pixels of higher conductivity around the inclusion, observed in the vertical view, could be caused by the data-model mismatch. The regularization assumes a continuous distribution and in fitting the step change in conductivity between the contrast and the prostate phantom, creates pixels of higher conductivity around the inclusion. With the reconstruction scheme we developed, we can tune the spatial resolution of the reconstruction by controlling the number and location of seed points. Using smaller pixels worsens the sensitivity in the pixels while larger voxels give better sensitivity. Using larger pixels theoretically betters the posedness of the problem as it improves the condition number of the inverse problem.

The height of the recovered contrast was estimated as the FWHM of the conductivity profile, shown in Figure 13, which was taken along the third column of pixels from the probe surface of the reconstructed image shown in Figure 13. The height of the recovered contrast was found to be 1.7 cm; which represents a 31% relative error from the actual height of 1.3 cm; however, as the heights of the pixels used in the reconstruction ranged between 0.8 cm and 0.9 cm, the location and dimensions of the localized contrast are within the error introduced by the chosen spatial resolution.

A cross-section taken perpendicular to this column of voxels is presented in Figure 12 (c).

Reconstructing the phantom data using the subvolume reconstruction algorithm is able to isolate the prostate volume but not the contrasts inside it, as illustrated in Figure 14. This is the expected result as the subvolume reconstruction algorithm doesn’t model the conductivity jump between the prostate and its surrounding tissue making it difficult to reconstruct contrasts within the prostate.

Other phantom studies where the inclusion was moved to higher and lower positions in the phantom were conducted; the reconstructions did not delineate the inclusion as well as the images shown in Figure 12, as we suffer from reduced sensitivity in these areas. In Borsic et al (2009) shows that the sensitivity at the top of the prostate is about 65% of the sensitivity at the prostate midpoint and the sensitivity at the base of the prostate is only about 4% higher than the sensitivity at the apex.
Figure 13 – Plot of conductivities along the third column of pixels for the reconstructed image shown in Figure 12 (b). The height of the inclusion was estimated as the Full Width at Half Maximum (FWHM) of this conductivity profile.

Figure 14 – Reconstructions shown in this figure were computed using the algorithm presented in (Wan et al. 2010). (a) Vertical cross-section of the difference reconstruction of the phantom shown in Figure 12 (a) (b) Axial view of the difference reconstruction of the phantom taken at cut-plane parallel to the center of the imaging volume (c) The color scale used for the images shown in Figure 13 (a) and (b).

6. CONCLUSIONS

The problem of reconstructing TREIT images is highly ill-posed due to the open-geometry nature of the problem. Furthermore, the inherently large difference in conductivity between the prostate and its surrounding tissue makes it difficult to identify contrasts within the prostate volume without the use of prior information. In this paper, we present a reconstruction scheme based on hard priors that restricts the estimation of electrical parameters to the prostate volume. Manual segmentations of US images are used to generate a surface representation of the prostate which is then incorporated into the
reconstruction. The presented reconstruction algorithm, based on using prior information, for imaging of the prostate shows promise for recovering contrasts within the prostate volume in the context of numerical simulations and phantom studies. In phantom studies, we experience difficulties in localizing the contrasts when the position of the inclusion was placed near the top or bottom of the phantom, as there is reduced sensitivity in these regions. In the future, we intend to augment the reconstructions by using variable sizes for the coarse voxels in different regions of the prostate, where sizing is based on the sensitivity of the regions. Voxel sizes can be controlled by using non-uniform spacing between seed points in the prostate volume. The results of this study show the value of using prior information in reconstructions. Particularly for the case of TREIT imaging, it presents a way of recovering contrasts inside the prostate volume which is useful for guiding prostate biopsies as it allows finer sampling in suspicious regions, as identified by the reconstructed images.

7. REFERENCES


Borsic A, Halter R, Wan Y, Hartov A and Paulsen K 2010 Electrical impedance tomography reconstruction for three-dimensional imaging of the prostate Physiol. Meas. 31 S1–16


Mimics 14 http://www.materialise.com/mimics


TetGen 1.4.3 http://tetgen.berlios.de/


