Mutual Information Based MREIT Reconstruction Using MR Anatomical Data

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Introduction:

As an adjunct to existing cancer detection techniques such as x-ray and MRI, Magnetic Resonance-Electrical Impedance Tomography (MREIT) has the potential to improve the specificity of current techniques because it is an imaging modality that measures tissue conductivity and it has been shown that the conductivity differs significantly among malignant, benign and normal tissues. A sensitivity based reconstruction algorithm with Tikhonov regularization has been successfully employed to resolve a complex and nested conductivity distributions [1]. In this work a mutual information based MREIT reconstruction algorithm was investigated to reconstruct the irregular conductivity distributions with improved accuracy.

Methods:

The injected currents inside an object will generate magnetic flux density; the component of the magnetic flux density in the main static field direction ($\mathbf{b}_z$) can be calculated from the MRI phase images using a modified spin echo pulse sequence [2]. To solve the conductivity distribution from the magnetic field measurement, the relationship between the perturbation of conductivity distribution ($\Delta\boldsymbol{\sigma}$) around an initial estimate (σ_i) and the resultant perturbation of the magnetic flux density ($\Delta\mathbf{b}_z$) can be linearized ($\Delta\mathbf{b}_z=\mathbf{S}\Delta\boldsymbol{\sigma}$) for a given current injection scheme. Here **S** is the sensitivity matrix that can be calculated analytically [3]. Due to the ill-posed nature of the sensitivity matrix **S** and noise in the data, regularization is required to solve the inverse problem of calculating $\Delta\boldsymbol{\sigma}$ from $\Delta\mathbf{b}_z$ and **S.** Including the Tikhonov regularization parameter λ, the matrix equations becomes $(\mathbf{S}^T\mathbf{S}+\lambda\mathbf{I})\,\Delta\boldsymbol{\sigma} = \mathbf{S}^T\Delta\mathbf{b}_z$ where **I** is the identity matrix, and the equation can then be solved using the conjugate gradient method. Previously λ was chosen to be the value that minimizing the difference between the measured magnetic flux density and the magnetic flux density calculated from the reconstructed conductivity. In this study we investigated mutual information based reconstruction methods [4] for MREIT. In the first approach, the λ value that maximized the mutual information between the calculated conductivity distribution image and the MR image was found. This is valid because mutual information is the measurement of nonlinear statistical dependency of two systems, and since both the MR image and conductivity image contain structural information about the tumor and the normal tissue, the mutual information between the two images should be maximized when the conductivity image is reconstructed most accurately.

Since the location and shape of the suspected lesions can be detected by MRI, one can generate an initial conductivity distribution with a two-compartment model that separates the suspected lesion and the normal tissue. This model will be a better approximation of the initial conductivity distribution (σ_i) instead of the standard approach of using a uniform σ_i. For the second approach, we first solve the inverse problem to find the conductivity values in these two compartments only, so a single conductivity value is calculated for each compartment. The resulting two-compartment conductivity map is used as the initial conductivity distribution in the second step and the equation above is solved to find the conductivity value for each pixel. Since this two-compartment σ_i is a better approximation, starting the iterative reconstruction from an initial condition closer to the actual values should yield more accurate conductivity maps and converge to the solution faster.

Results and discussion:

The same data acquired in the experiment described in [1] were used in the new reconstruction method. The reconstructed conductivity distribution using the original method in [1], the mutual information based reconstruction method with optimum λ (uniform initial conductivity), and the mutual information based reconstruction method with two-compartment initial conductivity distribution are shown in Fig.1. The two compartments were defined from the MR images that provide the contrast between compartments I and II in Fig.2. The reconstructed conductivities in the three cases were similar in general except in the regions marked by the red circles where substantial improvement was seen. Moreover, calculated conductivities from the mutual information based reconstructions were much closer to the actual values compared to the one calculated from the original method, where conductivity values turned out higher. Also note that the third compartment was successfully recovered although the σ_i was modeled with only two compartments. Therefore, it can be concluded that maximization of mutual information can be used as a criterion to reduce the uncertainty (such as estimation of the regularization parameter) in the MREIT conductivity reconstruction, thus the accuracy of the conductivity measurement can be improved by using the MR images as *a priori* information.

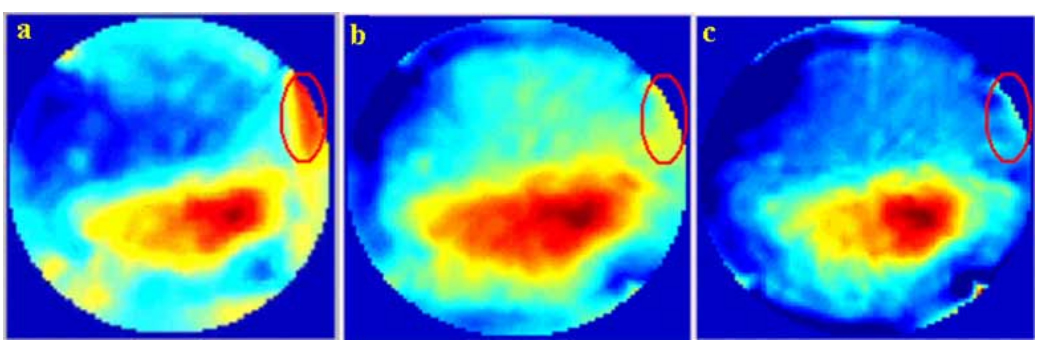

Fig1. The reconstructed conductivity distribution using the original method a), the mutual information based reconstruction method with optimum λ and uniform initial conductivity distribution b), and the mutual information based reconstruction method with two compartment averaged initial conductivity distribution c).

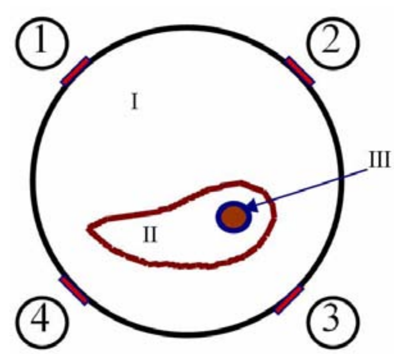

Fig 2. The schematic of the phantom with three nested conductivity compartments labeled I, II and III

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