A Software based Framework for Estimating Patient Displacement in Magnetic Induction Tomography

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Abstract-Magnetic induction tomography (MIT) is a contactless, inexpensive and non-invasive technique for imaging the conductivity distribution inside volume conductors. Time-difference imaging can be used for the monitoring of patients in critical care. This includes monitoring of cerebral strokes and breathing, as well as continuous screening of edema. However, MIT signals are much more sensitive to body movements than to the conductivity changes inside of the body. This is because small movements during data acquisition can spoil the signals of interest and cause significant image artifacts. Thus, it is crucial to accurately estimate and factor body movements into image reconstruction.

Methods: We proposed quantitative methods for identifying and estimating object movements from simulated MIT data prior to the image reconstruction step. A simulation was performed based on a 16 channel MIT system where a finite-difference based MIT software package was used to generate reference data from a homogenous tank without a target, and subsequent measurement of moved phantom with a target placed close to edge of the tank. The movement was estimated using frequency domain analysis (FFT).

Results: Results show that movements of 1% of the radius of the tank cause image blurring but the artifacts can be minimized by appropriate regularization. Higher amounts of movements totally distorted the images which require artifact compensation or acquisition of new measurements. The percentage errors for FFT based movement estimation were 23% (1 mm), 0.3% (6.7 mm) and 6% (14.4 mm) for a displacement of 1% (1.3 mm), 5% (6.7 mm) and 10% (13.5 mm), respectively, where the displacements were chosen relative to the radius of the tank. It was found that the accuracy of movement estimation is related to the size of the background in real measurements.

1. INTRODUCTION

Magnetic Induction Tomography (MIT) is a relatively new, non-invasive technique for imaging the distribution of the electrical properties (conductivity, permittivity and permeability) of objects. MIT was proposed for numerous medical applications such as monitoring of cerebral stroke, breathing (aeration and ventilation of the lung) and continuous screening of edema [1].

Time-difference imaging can be used for monitoring the progression of the stroke, breathing or oedema to be used for continuous screening and monitoring of patients in critical care. However, it is a challenging task to do accurate measurements and to post-process the data properly in the emergency care unit since it is a highly dynamic scenario [2]. Small movements can spoil the measured data and cause significant image artifacts, which prevent the detection of the conductivity changes inside of the body. Static imaging may not reflect the dynamics of objects in monitoring applications. Especially, artifacts associated with motion of head and functional imaging of lung require keeping track the motions and compensating the artifacts.

In other tomographic fields such as CT or EIT, various software and hardware based movement detection approaches and management strategies can be grouped into two categories. First category can be named as the software based (signal/image processing) approach that may include pattern recognition, eigenvalue analysis (ICA, PCA), neural networks, edge detection and level set methods. Second one is the hardware approach and includes pressure sensitive mattresses, recording of patient movement via magnetic or optical sensors. The choice of the techniques is generally dependent on the application. For instance, considering a smart-bed application, pressure sensitive mattresses are more suitable, but a system based on a video recording or stereo tracking of patient movement is an alternative if other techniques are not appropriate. Gürsoy and Scharfetter proposed strategies for compensating patient movement in MIT based on a priori information [3].

MIT is a low resolution imaging technique that estimation and compensation of motion artifacts in MIT are a challenging task as this requires new approaches and measurements needs to be fast processed to detect movements [4]. The goal of this paper is to estimate the movements and compensate to improve image stability and improve image quality, particularly for the continuous monitoring of patients. Based on a preliminary study, a quantitative method were proposed for identifying and estimating object movements from simulated MIT data prior to the image reconstruction step. The software based movement estimation includes frequency domain analysis (FFT). The management strategies include reconstructing images by (i) minimizing movement artifacts for small movements; (ii) compensating for the movements if these are accurately estimated, or (iii) taking a new MIT measurement if movements are too severe.

2. METHODOLOGY

A. Overview

In this paper, algorithmic methods were proposed for identifying and estimating object movements from simulated MIT data prior to the image reconstruction step. In time or frequency domain, the measured raw data from each individual sensor is preprocessed or post-processed using those concepts in digital signal processing, which include FFT, advanced statistical approaches (ICA) or wavelet based approaches.

B. Phantom

The homogenous tank (radius of 13.5 cm and height of 20 cm) has the conductivity of 1 Sm^{-1}, and the small cubic target has the conductivity of 3 Sm^{-1}. A simulation was performed based on a 16 channel MIT system. A finite-difference based MIT software package was used to generate (i) reference data without a target and movement, and (ii) simulate whole tank movement with a target placed close to edge of the tank.

C. MIT image reconstruction

A Newton-type algorithm with Tikhonov regularization is applied to solve the inverse problem which is written as,

$$\Delta\boldsymbol{\sigma} = (\mathbf{S}^T\mathbf{S} + \lambda\mathbf{I})^{-1}\mathbf{S}^T\left[\frac{(\mathbf{V}_i - \mathbf{V}_r)}{\mathbf{V}_r}\right] = \mathbf{S}^T[(\mathbf{S}\mathbf{S}^T + \lambda\mathbf{I})^{-1}\Delta\mathbf{V}] \tag{3}$$

where $\Delta\boldsymbol{\sigma}$ is the change of the conductivity, λ is the regularization parameter, $\mathbf{I}$ is the identity matrix, S sensitivity matrix (Jacobian), and $\Delta\mathbf{V}$ is the difference between a reference signal $\mathbf{V}_r$ and subsequent measured signal $\mathbf{V}_i$. The size of $\Delta\mathbf{V}$ is equal to the number of measurements (precisely the excitation and detection coil combinations).

An appropriate selection of λ is important in image reconstruction and it can be seen as a low-pass filter from a signal processing perspective. There is a trade-off between improving resolution and avoidance of noise amplification. More commonly used methods for estimating λ are L-curve method, generalized cross validation (GCV) and Morozov's discrepancy principle.

D. Signal analysis

Movements cause the changes/distortion in MIT signals, which means both the phase and magnitude in frequency domain are correspondingly distorted as well. The strength of the distortion due to the movement is proportional to the size of dislocation. Following algorithm is implemented to estimate the dislocation of a body:

i. Find the phase change after the movement ($\Delta\mathbf{V}_m$)
ii. Find the FFT for both $\mathbf{V}_r$ and $\Delta\mathbf{V}_m$
iii. Find the peaks (main index) from $\Delta\mathbf{V}_m$ and use it as an index value due to the movement
iv. correlate them using the index value in both $\mathbf{V}_r$ and $\Delta\mathbf{V}_m$ in frequency domain (magnitude of movement / magnitude of normal signal)
v. Multiply with a certain factor (i.e. *10) which is related to the size of a tank in real measurement.

3. RESULTS:

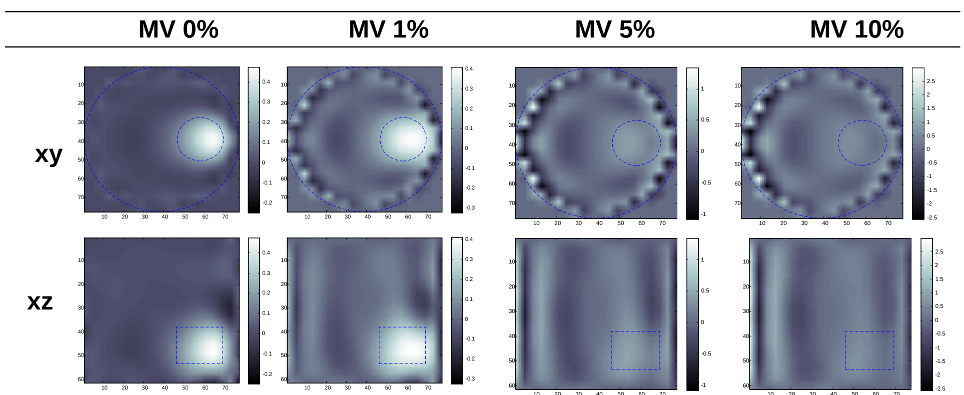

Fig. 1: Reconstructed images with movements of 1% (1.3 mm), 5% (6.7 mm) and 10% (13.5 mm) relative to the radius of the tank. Note: MV stands for movement, row 1 is for xy plane and row 2 is for xz plane.

The proposed method equally works well on both measured raw signals through preprocessing and reconstructed images through post-processing, so only post-possessing results are presented. The results in Fig. 1 show that there are certain correlation between the distortion magnitude and the size of movement with larger distortion with increasing movement size.

Fig. 2 shows the effect of regularization (filtering) value and the non-negativity constraint. The row one is for the reconstructed images with 1% movement and row two is for 5 % movement, and columns is for increased regularization. It can be seen that the increased regularization (filtering) reduced certain movement noise (row 2) and a smooth object appeared, but it also get rid of useful information in row 1 which leads to losing of spatial resolution.

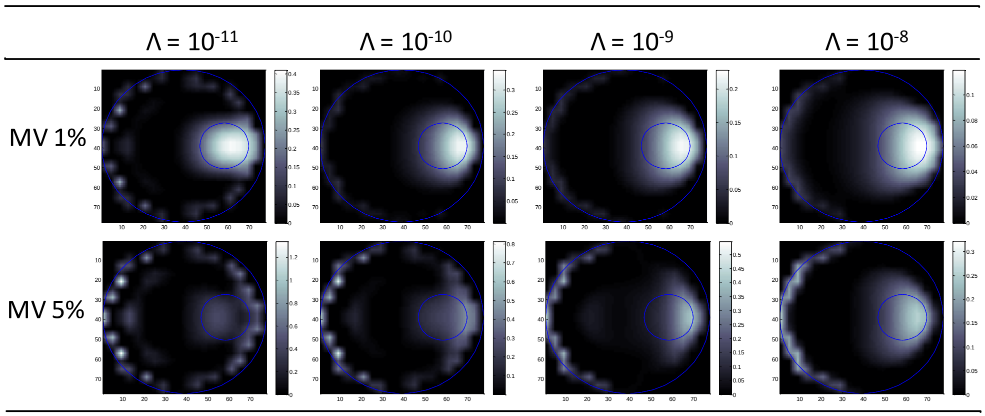

Fig. 2: Reconstructed images with varying the regularization (filtering) value and the non-negativity constraint.

Fig. 3 shows the reconstructed images after eliminating the movement artifact based on a priori information. For known amounts of movement, the image artifacts can be suppressed.

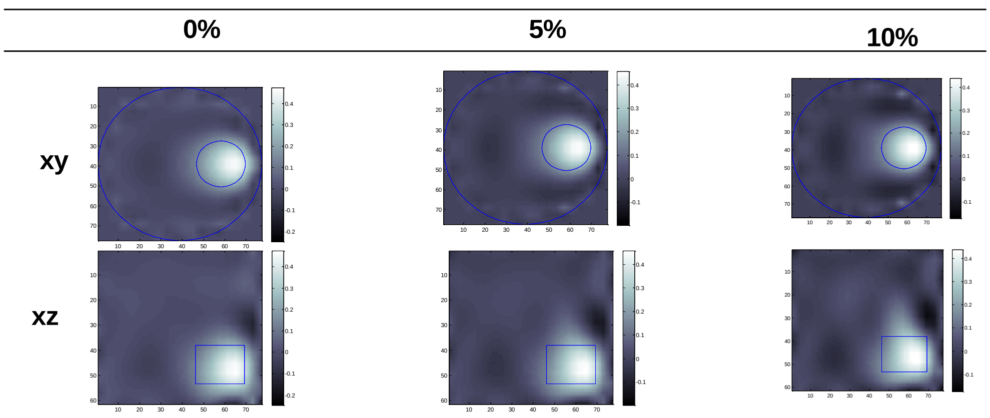

Fig. 3: Reconstructed images after movement artefact compensation using a priori information.

Table 1 presents the estimated movement and percentage error for 3 types of movements.

Table 1: Estimated movement and percentage error (movement in mm).

Original movement	Estimated movement	Percentage error (%)
1.3 (1%)	1	23
6.75 (5%)	6.73	0.3
13.5 (10%)	14.4	6

4. DISCUSSIONS and CONCLUSIONS

In this paper, the effect of body displacement for signal and image quality was investigated, and quantitative methods and algorithms were proposed to estimate the displacement to identify and compensate imaging artifacts caused by the displacement. An FFT based approach was evaluated for the movement estimation due to its simplicity in discriminating signals from noise. Frequency analysis provides hints about the motions, since the upper and lower frequency sideband components appear as ghosts either side of the primary image. The percentage errors for FFT based movement estimation were 23%, 0.3% and 6% for movement of 1% (1.3 mm), 5% (6.7 mm) and 10% (13.5 mm) of the radius of the tank. Studies also showed that movement less than 2 % blur the image but the artifacts can be minimized by regularization approach without artifact compensation or taking new measurements.

The accuracy of the movement estimation was found to be related with the size of the background in the real measurement study. Following management strategies are proposed once movements are identified, images are reconstructed by (i) minimizing movement artefacts for small movements; (ii) compensating for the movements if these are accurately estimated, or (iii) taking a new MIT measurement if movements are too severe.

For certain applications, multi-frequency measurement and absolute imaging can be used since they are not affected by the movement under a criterion that the movement is taken place in two separate measurements not during the measurement. Although multi-frequency MIT may offer advantages in terms of reducing movement artefacts and provide more useful diagnostic information for medical applications, the frequency dependences of MIT received signal is a major limitation.

Measurement noise and image artifacts caused by the body displacement are a major problem in patient monitoring that makes it challenging to acquire accurate measurement and perform post-processing properly. The framework could help improve the stability of MIT measurements for a long period and produce better reconstructed image quality. The advantages of the software approach compared to hardware approach are faster processing and cost-effectiveness as it does not require any extra hardware. A further study will be conducted using statistical and wavelet approaches under this framework, and further movement will be tested in both simulation and reality to provide dynamic compensation.

REFERENCES

1. Griffiths, H., “Magnetic induction tomography,” *Measurement Science & Technology*, 12: 1126-1131, 2001.
2. Y. Maimaitijiang, M.A. Roula and J. Kahlert, "Approaches for improving image quality in magnetic induction tomography," *Physiol. Meas*. 31 (2010) S147-S156.
3. Gürsoy, D., and H. Scharfetter, “Reconstruction artefacts in magnetic induction tomography due to patient's movement during data acquisition,” *Physiological Measurement*, vol.30, no.6, pp.165-S174, 2009.
4. Y. Maimaitijiang, H.C. Wee, S. Watson, M. A. Roula, R. Patz, R. J. Williams “Evaluations of Parallel FFT Implementations on GPU and Multi-core PCs for Magnetic Induction Tomography,” World Congress on Medical Physics and Biomedical Engineering (WC2009), Munich, Germany, 2009.