# Improving Image Quality for Stroke Imaging in Magnetic Induction Tomography

Mamatjan Yasin[1], Ali Roula[2], Kurban Ubul[3] and Andy Adler[1]
1. Carleton University, Ottawa, K2E7E8, Canada; {mamatjan,adler}@sce.carleton.ca
2. University of Glamorgan, Pontypridd, CF371DL, UK; maroula@glam.ac.uk
3. School of Information Science and Engineering, Xinjiang University, Urumqi, China

**Abstract.** Magnetic Induction Tomography (MIT) imaging technique has the potential of providing an inexpensive, easy to use Medical Device for continuous screening and monitoring of patients in emergency and critical care. For instance, MIT could be used to detect hemorrhagic stroke in the brain, if high measurement accuracy and spatial resolution can be reached to allow significant contrast between normal brain tissues and hemorrhaged areas. However, this can be challenging because (i) spatial resolution in MIT is limited due to the small number of independent measurements, and (ii) erroneous data causes large artifacts in reconstructed images and thus lower the detectability threshold of bleeding as well as physiological tissue changes. The noise components that degrade the signal and image quality may be caused by thermal drift and noise from the acquisition system, by body movements ( body dislocation, heart rate, respiration), unspecified physiological (e.g. body temperature, sweating) and environmental changes. The objective of the paper is to improve the imaging stability and generate higher image quality in order to monitor stroke patients for a long period of time. Three approaches are used such as (i) level setting, (ii) spatial low pass filtering, (iii) averaging of multiple measurements as well as various combinations of these approaches. We have experimentally tested these methods with in vitro phantom resembling a cerebral stroke based on 15 ml bleeding within a biomembrane package placed in a 100 ml of pig brain. The results showed that these approaches greatly improved the image quality and the localization of phantom hemorrhages such that their combination produced the best results. These methods may make it easy to clinical interpretation and can be used to long term monitor the stroke patients.

Keywords: Magnetic Induction Tomography, level set, spatial filtering, cerebral stroke, patient monitoring

## 1. Introduction

Magnetic Induction Tomography (MIT) is a new non-invasive technique for imaging the distribution of the electrical properties (conductivity, permittivity and permeability) of objects [1]. MIT systems typically comprise electronic front end components (excitation and sensing systems) and a computer based data processing system. An overview of a typical MIT system is shown in Fig. 1. MIT has been proposed for numerous medical such as stroke and lung imaging [1]. Advantages of MIT are portable, low-cost, non-invasive, low-risk to a body, and its ability to characterizing biological tissues or biological objects through spectroscopy.

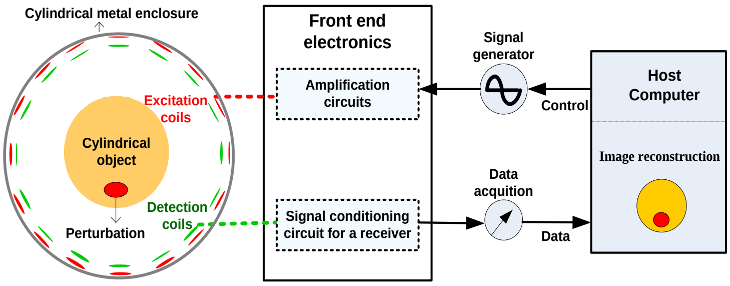


Fig. 1 A simplified diagram of the MIT system (left) in a plan view

The first experimental multi-channel MIT system was designed by Korjenevsky *et al* [2] for biomedical applications with system frequency of 20 MHz. Watson *et al* [3] designed a lower frequency (10MHz) 16 channel MIT system for use in low conductivity samples. A similar annular-array 16 channel MIT system was developed by Hamsch *et al* [4] using down-conversion methods with a capability of simultaneous parallel readouts for cerebral stroke applications. However, in MIT, it is a challenging task to reconstruct images with high data accuracy due to a poor signal to noise ratio (SNR). The SNR is not only determined by random background noise, inherent system noise and severe drifts due to temperature dependent behavior of receive channel, but also by a systematic signal degrading by several reasons in long term monitoring applications. Especially, dynamic changes caused by system instabilities and unspecific physiological changes in the subject makes it challenging to do accurate measurements and to post-process the data properly. Due to the corrupted data, in most cases, the reconstructed image contains artifacts.

The paper aims to improve the stability and accuracy of MIT measurements and generate higher image quality in the continuous monitoring of stroke patients and screening of edema for a long period of time. Three approaches were implemented to improve measurement accuracy and image quality based on (i) level setting, (ii) spatial low pass filtering, and (iii) averaging of multiple measurements. In the result and conclusion sections, reconstructed images are compared and discussed based on original image versus the proposed methods and their combinations.

## 2. Methodology

### A. MIT system and evaluation overview:

The MIT system in Fig. 1 comprises electronic front end components, and a computer based modeling and data processing system. The former is used to excite the sample space to be imaged with an alternating magnetic field and then sense changes in the signal resulting from the sample presence (i.e. stroke). The computer system is used to process the sensed data and to generate an image of the sample space representing its conductivity distribution. The MIT measurement system consists of an annular-array 16 channel MIT system and used down-conversion methods with a capability of simultaneous parallel readouts of 16 receiver channels. The MIT system operated at 10 MHz [4].

This paper will only focus on the newly developed methods due to space limitations. Details of the MIT forward model and reconstruction algorithms can be found in [5]. The implementation of all algorithmic aspects of this work used the Matlab language. We proposed three approaches to improve image quality and have localized object detection when compared to conventional reconstruction without pre/postprocessing. These approaches are (i) level setting, (ii) spatial low pass filtering, and (iii) averaging of multiple measurements. We experimentally evaluated them using the MIT system and phantoms in two different scenarios.

### B. MIT measurement protocols:

*Case 1 – in vitro tissue for stroke detection:* We used in vitro tissue resembling peripheral hemorrhagic cerebral stroke where 15 ml blood in a plastic package (to avoid the blood leaked into the brain tissue) was placed in a swine brain of 100 ml (inside a bottle with 9.4 cm diameter and 16 cm high) as shown in Fig. 2. A swine brain of 10 ml is placed in a cavity which was open the side of the bottle. The swine brain has conductivity of 0.32 S/m, while the blood has conductivity of 0.97 S/m. The conductivity of materials was measured using an Agilent 4294A impedance analyzer. The time interval between successive measurements is set to 16 seconds. A series of consecutive measurement sequences are taken while a single reference measurement is used. Experimental data was taken at 0, 5, 10, 30 minute slot to check the detectability of MIT for monitoring application.

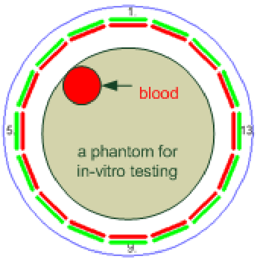


Fig. 2 A phantom for in-vitro testing of bleeding in the brain

*Case 2 - phantom measurement for long term monitoring:* The coagulated blood was found to have a lower conductivity in case 1 and is harder to be detected by MIT after certain period of time. To avoid tissue degeneration for long time monitoring, a tank was filled with a liter of half saline and half agar of the same conductivity (0.2 S/m) and cooked cubic agar phantom (5 ml, 0.6 S/m) was prepared and placed in the tank in the central plane at the lower corner as shown in phantom section of Fig. 1.

**C. Pre-processing with averaging of measurements:** Measured raw data is averaged over 5 to 10 data sequences to improve measurement precision by reducing random electronic noise and improving measurement SNR. This in turn may produce more stable reconstructed images. However, it takes 16s to obtain one frame of MIT measurement data with a combination of 16 excitation × 16 detection channels.

**D. Post-processing with Low-pass spatial filtering:** Spatial filtering is used to smoothen reconstructed images by penalizing strong artifacts which often exhibit high spatial frequency while attempting to preserve image informational content. This is achieved by applying low-pass masks to each pixel in the image as described in Fig. 3.

```
Define the filter value (f)
Calculate mean (m) and standard deviation values (s)
for i from 1 to n
  if absolute (image(i) – m)  > ( f * s) then
    Find neighbors according to FEM model
    Image(i) = sum of neighboring image pixels (i) / number of neighbors
  end
end
```

Fig. 3 Pseudo-code for low-pass spatial filtering. f is the filter level, n is the total number of image pixels

**E. Post-processing with level setting:** Level setting method is used to eliminate random artifacts and adjust the energy level threshold of reconstructed image value to be displayed as an output image. The pixel values are capped using a threshold value that is a ratio of the image's maximum value and the rest was eliminated by setting them to zero. The ratio value was set to 75% in this paper. This value was empirically found to keeps most of the wanted image while reducing most of the unwanted noise and artifacts. However, it can be tuned depending on the application and noise level in the MIT hardware.

## 3. Results

Case 1 – in vitro tissue for stroke detection: Fig. 4 shows the reconstructed images on 15 ml bleeding within a biomembrane package placed in a 100 ml of pig brain as a detectable bleeding case. Four consecutive measurement sequences are evaluated. The following cases are compared (i) original reconstruction, (ii) level setting, and (iii) level setting plus spatial filtering.

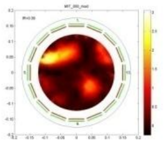
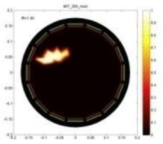
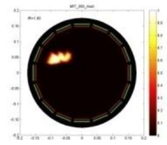
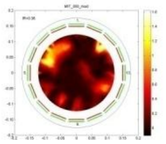
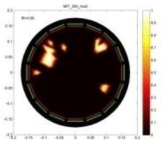
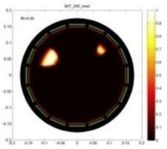
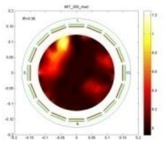
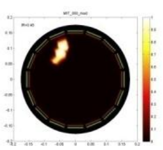
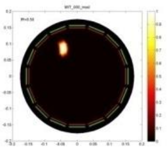
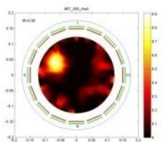
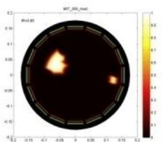
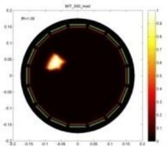
| Measurement sequences | Original (i) | Level setting (ii) | Level setting + spatial filtering (iii) |
|---|---|---|---|
| 1 |  |  |  |
| 2 |  |  |  |
| 3 |  |  |  |
| 4 |  |  |  |

Fig. 4 Reconstructed images based on: (i) original reconstruction (ii) level setting, and (iii) level setting and spatial filtering. (Note: All the reconstruction are performed with the fixed regularization of $\lambda=10^{-9}$)

It can be seen from Fig. 4 that large artifacts appeared in original reconstructed images. Level setting approach filtered out most of the artifacts and produced clear reconstructed images. A further improvement is achieved by combining level setting with spatial low-pass filtering. This cancelled the remaining small image artifacts that level setting alone only could not removed.

Fig. 5 shows the reconstructed images on 15 ml bleeding within a biomembrane package placed in a 100 ml of pig brain. It shows (i) original reconstruction, (ii) averaging of 5 measurements, (ii) averaging of 10 measurements, and (iv) averaging of 5 measurements plus level setting and spatial filtering. All reconstructions are performed with a fixed regularization parameter ($\lambda=10^{-9}$).

The three original image reconstructions in Fig. 5 show that drift and noise have a great effect on the image quality. The averaging of five measurements and ten measurements suppressed random artifacts due to the noise and produced more stable reconstructed images as shown in Fig. 5. The level setting and spatial low-pass filtering approach further improved the image quality by clearing the artifacts below the defined threshold.

| Original<br>(i) | Averaging 5 measurements<br>(ii) | Averaging 10 measurements<br>(iii) | Averaging 5 + level setting + spatial filtering<br>(iv) |
|---|---|---|---|

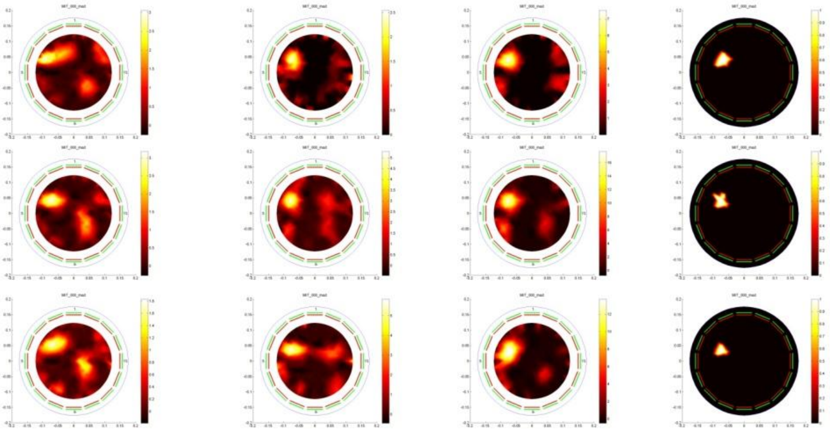


Fig. 5 Comparison of reconstructed images based on: (i) original reconstruction, (ii) averaging of 5 measurements, (ii) averaging of 10 measurements, and (iv) averaging of 5 measurements plus level setting and spatial filtering

**Case 2 - phantom measurement for long term monitoring:**

| Time (in minutes) | 8 | 18 | 38 | 68 |
|---|---|---|---|---|

Original reconstruction

Level set and spatial filtering

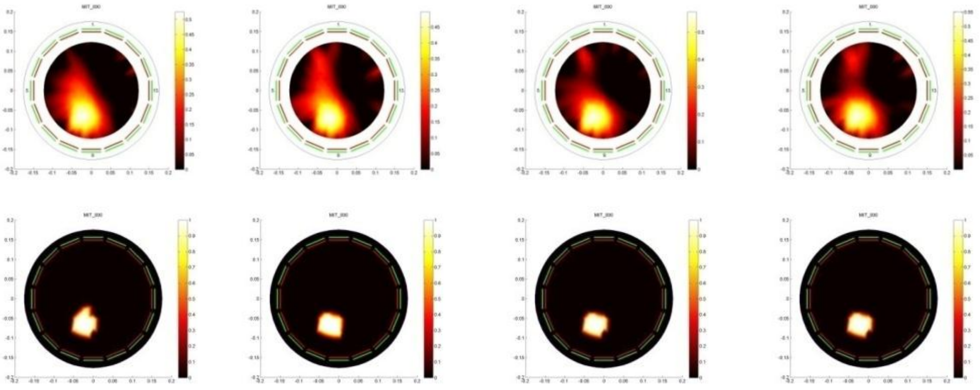


Fig. 6 Level set and spatial filtering assisted monitoring using phantom measurement

It can be seen from the Fig. 6 that the level setting and spatial low-pass filtering approaches also helped improve image quality and membrane detectably over multiple measurements while original reconstruction showed artifacts.

## 4. Discussions and Conclusions

In this paper, we tested and compared approaches for improving the measurement signals and image reconstruction: (i) level setting, (ii) spatial low pass filtering and (iii) averaging of multiple measurements. For this paper, the random noise from the MIT electronic components was considered to be the source of noise, as the rest of noise is ignored. Although for a typical clinical situation such as hemorrhagic stroke detection, the reference measurement is not usually available, the time-difference measurement can be useful to monitor if the aim is to detect bleeding after brain surgery or after a prescribed clot-busting drugs is administered -typically TPA to the patients with ischemic stroke which may also cause bleeding in the brain. The MIT system suffered from the measurement noise and drift. For the first 1.5 hours, temperature drift coefficient was measured at 11.7 (milli Degree/C°) and averaged phase standard deviation was 26.3 (milli Degree).

The level setting, spatial filtering and averaging approaches as shown in Fig. 4 and 5 helped to improve image quality and reduce noise by preserving the edges and reducing artifacts. Image quality improved with averaging of multiple measurements on both reference measurements and real measurements. The spatial low-pass filtering approach further improved the reconstructed image quality by getting rid of small image artifacts from the reconstructed image using Level setting approach. A combination of measurement averaging followed by level setting and spatial filtering appear to produce the best results. Phantom measurement with the same methodology (Fig. 6) produced more stable results than the in vitro tissues resembling cerebral stroke in Fig. 4.

If the bleeding is strong and above the detectability threshold of the system, most of artifacts can be removed. Although the averaging method produces better SNR values for this study, it is not practical for monitoring applications because the MIT data acquisition for a full data frame (16 excitation × 16 detection channels) takes 16s. A fast data acquisition system was achieved by Maimaitijiang et al [5], therefore exploiting advanced hardware and parallel algorithms could be an option to achieve fast MIT system.

If the bleeding is at the detectability threshold of the system, not all artifacts may be reduced. Sometimes artifacts may be multiplied in such a way that they may appear like a bleeding. This is often called false positive and should be avoided. One way of doing so would be to take a priori information into account or take new measurements. The a priori information can be threefold: (i) patient specific anatomical information, (ii) redundant information from recent scans, (iii) system specific behavior on noise and signal degradation. Wavelet based denoising algorithms with adaptive regularization [6] were found to be an effective means to lower the detectability threshold and improve image quality while hardware improvement [7] and combined multi-modality approaches [8] were proposed for improving measurement accuracy and image quality respectively.

Measurement noise and image artifacts are a major problem in many patient monitoring and imaging applications because dynamic changes caused by system instabilities, environmental changes and unspecific physiological changes in the subject makes it challenging to do accurate measurements and to post-process the data properly. The proposed software approaches can be easily combined and integrated to the MIT image reconstruction system. This may simplify clinical interpretation in terms of bleeding volume and progress of stroke as well as it can be used to do a long term stable monitoring of patients. For our future work, firstly, image quality will be evaluated in quantitative terms using GREIT [9] which illustrates several figures of merits that are useful for our study; secondly, better system calibration and dynamic recalibration methods will be investigated to improve the measurement and its robustness.

## 5. Acknowledgment

The author would like to thank to Daniel Chen from Philips Shanghai for their support and fruitful discussions.

## References

[1] Griffiths H (2001) Magnetic induction tomography. Measurement Science & Technology, 12: 1126-1131.

[2] A. Korjenevsky, V. Cherepenin, and S. Sapetsky, "Magnetic induction tomography: experimental realization," Physiological Measurement, vol. 21, pp. 89-94, 2000.

[3] Watson S, Williams R J, Gough W and Griffiths H, (2008) "A magnetic induction tomography system for samples with conductivities below 10 S m-1, " Meas. Sci. Technol. **19** 045501 (11pp).

[4] Vauhkonen M, Hamsch M, Igney CH (2008) A measurement system and image reconstruction in magnetic induction tomography. Physiol. Meas., vol. 29, pp. S445–S454, DOI:10.1088/0967-3334/29/6/S37.

[5] 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.

[6] Y. Maimaitijiang, M.A. Roula and J. Kahlert, "Approaches for improving image quality in magnetic induction tomography," *Physiol. Meas.* 31 (2010) S147-S156.

[7] Wee, H.C., Watson, S., Patz, R., Griffiths, H., and R.J. Williams, A Magnetic Induction Tomography system with sub-millidegree phase noise and high long-term stability, IFMBE Proceedings of the 4th European Conference, Antwerp, Belgium, p. 744 – 747, 2008.

[8] D. Gürsoy, Y. Mamatjan, A. Adler and H. Scharfetter, "Enhancing impedance imaging through multi-modal tomography," to appear in *IEEE Transactions on Biomedical Engineering*, 2011.

[9] A. Adler et al "GREIT: a unified approach to 2D linear EIT reconstruction of lung images," Physiol. Meas. 30 S35-S55, 2009.