Pre-processing of data using logarithmic transformation to improve the spatial resolution of an EIT system for biomedical applications

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Abstract. One of the major applications of EIT is in medical imaging where low values of current are injected at low frequencies owing to safety concerns. Due to low values of injected current, the differences between the boundary voltages are quite small, especially as we go farther from the injected electrodes. In this paper we propose the use of logarithmic transformation to increase the difference between the boundary data, making them distinguishable enough for high resolution imaging. Simulation and practical phantom experiments are carried out and the reconstructed images are analysed before and after the logarithmic transformation. Results are also compared with the pre-processing technique based on root transformations. Limitations of the proposed logarithmic transformation technique are also discussed.

1. Introduction

Electrical Impedance Tomography (EIT) is an imaging technique used to detect changes in conductivity inside a region by using measurements through surface electrodes [1]. Being a low cost, real-time monitoring system, it is widely used in several areas like medical imaging, industrial processing and geophysics [2]. In medical applications of EIT, the boundary voltages lie in a very small dynamic range due to low values of injected current. Also, as we go farther from the injected electrodes, the difference between the boundary voltages is almost indistinguishable. Poor spatial resolution of an EIT system is due to the low signal to noise ratio and the small dynamic range of the measured data [3,4]. For high resolution imaging, boundary voltages should be distinguishable enough [5,6]. It has been reported earlier that linear transformation, such as amplification of the signal, increases the difference between the boundary voltages but this also amplifies the noise [7].

Logarithm function expands lower values and compresses higher values. This paper presents the use of logarithmic transformation to expand small differences between the boundary data, thereby increasing the spatial resolution. It also improves the signal to noise ratio as will be discussed later.

Simulation studies and phantom experiments are carried out to evaluate the use of the proposed transformation technique. Reconstructed images are analysed using image analysing parameters like Resolution (RES), Contrast to Noise Ratio (CNR) and Position Error (PE). The proposed methodology is compared with the pre-processing technique that uses roots of the measured data [7].
The EIT principle and system design is explained in the next section. The third section describes the proposed methodology and the relative size index parameter which is a measure of the difference between the boundary measurements. The proposed transformation technique is further evaluated and compared with the pre-processing technique based on root transformations. To analyse the effect of the proposed methodology on the reconstruction, simulation, as well as phantom experiments carried out, are discussed in the fourth section. The paper ends with the conclusion.

2. Materials and Methods

2.1. Imaging Principle
An EIT system comprises the electrodes attached to the surface of the body whose conductivity is to be mapped. Low frequency alternating currents are injected through the electrodes. This produces electric field inside the body. In EIT, measured voltages are a nonlinear function of conductivity and current as [1]:

\[ V = f(\sigma, I) \]  

(1)

During reconstruction, conductivity distribution \( \sigma \) is estimated from the boundary voltages as [1]:

\[ \sigma = S^{-1}V \]  

(2)

Where \( S \) is the sensitivity matrix related to conductivity change.

2.2. Data acquisition system design:
An EIT system is developed, consisting of a constant current injector based on Howland current source with grounded load [8], multiplexers to switch between the electrodes, a signal conditioning circuit involving a high pass filter to remove any offset introduced due to electrode-electrolyte contact impedance followed by a difference amplifier. The boundary voltages are firstly filtered using a high pass filter and then fed to an instrumentation amplifier with unity gain to obtain differential voltage. Data is acquired through LabView using a Data Acquisition card from NI whose sampling frequency is set at 200KS/s. The adjacent method is used for current injection where current is injected into a pair of electrodes and voltages are measured on the remaining pair of electrodes [9]. With 16 electrodes, for each excitation there are 13 measurements and hence a total of 208 channels.

2.3. Phantom Design:
A plastic circular tank, 20cm in diameter is filled with saline solution. Sixteen electrodes, made of stainless steel and 1cm in width each, are attached to its inner surface. The phantom is connected to the data acquisition system by an FRC cable attached to the electrodes. A non-conducting cylindrical object is introduced into the saline solution for 2D imaging.

3. Proposed Methodology for Pre-processing
The acquired data can be represented as:

\[ x = [x_1, x_2, x_3, \ldots, x_n] \]  

(3)

where, \( n \) is the total number of channels. The data \( X \) is transformed non-linearly to a new data set \( Y \) using logarithmic transformation as below:

\[ y = \log(x) \]  

(4)

And the new data set \( Y \) is used for reconstruction which results in improved signal to noise ratio as well as a greater difference between boundary voltages.
It can be mathematically shown that if log transformation is carried out on a noisy signal, it improves the signal to noise ratio as derived below.

EIT signal corrupted with noise can be represented as:

\[ x_i = s_i + n_i \]  \hspace{1cm} (5)

where, \( s_i \) is the signal and \( n_i \) is the noise and the signal to noise ratio is \( \frac{s_i}{n_i} \).

Logarithm of the signal is represented as:

\[ \log x_i = \log(s_i + n_i) \]  \hspace{1cm} (6)

Or \[ \log x_i = \log \left( \frac{s_i + n_i}{s_i} \right) \]  \hspace{1cm} (7)

Or \[ \log x_i = \log s_i + \log \left( 1 + \frac{n_i}{s_i} \right) \]  \hspace{1cm} (8)

Using Taylor Series Expansion,

\[ \log x_i = \log s_i + \left[ \frac{n_i}{s_i} - \frac{n_i^2}{2s_i^2} + \frac{n_i^3}{3s_i^3} - \frac{n_i^4}{4s_i^4} + \cdots \right] \]  \hspace{1cm} (9)

Equation 9 can be represented in terms of a transformed Equation as:

\[ y = s' + n' \]  \hspace{1cm} (10)

where signal is \( s' \), which is equal to \( \log s_i \) and noise is \( n' \) which is reduced to \( \left\{ \frac{n_i}{s_i} - \frac{n_i^2}{2s_i^2} + \frac{n_i^3}{3s_i^3} - \frac{n_i^4}{4s_i^4} + \cdots \right\} \).

Since \( s_i > n_i \), the term \( \left\{ \frac{n_i}{s_i} - \frac{n_i^2}{2s_i^2} + \frac{n_i^3}{3s_i^3} - \frac{n_i^4}{4s_i^4} + \cdots \right\} \) will always be less than \( n \).

Due to the low value of injected current, the measured boundary voltages usually lie in a range between 0 and 1. As per the property of log

\[ |\log a| > |a| \text{ for } a < 1 \]  \hspace{1cm} (11)

As per equations 10 and 11, the signal increases to \( \log s_i \) and the noise reduces to \( \left\{ \frac{n_i}{s_i} - \frac{n_i^2}{2s_i^2} + \frac{n_i^3}{3s_i^3} + \cdots \right\} \). This shows that the log transformation will improve the signal to noise ratio.

In EIT, due to low values of injected current, the developed voltages lie in a small range and hence the difference between boundary measurements is much less, especially as we go farther from the injecting electrodes, which makes them indistinguishable as shown in Figure 1. The property of logarithm is such that higher values are compressed and lower values are spread [10]. Log transformation of the measured data increases the difference between the boundary voltages for EIT which is otherwise very low, thus making them distinguishable.

Two circular in-homogeneities in a circular tank with sixteen electrodes on its circumference are simulated in EIDORS as shown in Figure 1(a). The background conductivity is taken as 0.8S/m and for circular in-homogeneities it is 0.6S/m.

Figure 1(b) shows measured data before and after the proposed log transformation and rooting based non-linear transformations. Figure 1(c) shows measured data for single excitation. The difference between the boundary data decreases as we go farther from the injected electrodes and is least for the electrode pairs opposite to the injected pair. This is shown as \( \Delta V \) in Figure 1(c).
Figure 1. (a) Simulated model in EIDORS, (b) measured data before and after non-linear transformation (c) measured data for single excitation.

Table 1. ΔV values before and after non-linear transformations.

| Measured data type | ΔV     |
|--------------------|--------|
| Raw_data           | 0.00070|
| Square root        | 0.00269|
| Fifth root         | 0.00277|
| Fifteenth root     | 0.00121|
| Fifteenth root     | 0.00040|
| Log                | 0.04000|

Table 1 shows the value for ΔV before and after non-linear transformations. It is observed that ΔV increases up to fifth root and then starts decreasing. Log transformation gives the highest value for ΔV.

Relative size index is used to compare the proposed methodology based on logarithmic transformation with the pre-processing technique that uses roots of the measured data. It is the measure of the difference between the boundary measurements and the higher the Relative Size index the better the spatial resolution will be [6]. We have calculated Relative Size index as follows:

\[
RS = \sum_{i=1}^{n} \sum_{j=1}^{k} [\max\{v_{ij}, v_{i,j+1}\} - \min\{v_{ij}, v_{i,j+1}\}] \quad i = 1,2,3,...,n \quad j = 1,2,3,...,K
\]

where, \(v_{ij}\) is the \(j^{th}\) measurement for \(i^{th}\) excitation.

Table 2 shows the Relative size index before and after pre-processing of the data for the simulation shown in Figure 1(a).

| Measured data type | RS     |
|--------------------|--------|
| Raw_data           | 0.325  |
| Square root        | 0.680  |
| Fifth root         | 0.460  |
| Fifteenth root     | 0.688  |
| Fifteenth root     | 0.070  |
| Log                | 6.260  |
Log transformation results in a considerable increase in the RS index as compared to root transformations.

4. Experiments

4.1. Simulations using EIDORS

A 2D circular model with 16 electrodes on the surface is created in EIDORS. Noise is added to the simulated model with 12 dB of SNR as the worst case reported data for practical EIT systems [11]. EIT images are obtained before and after pre-processing of the measured data. Background conductivity is chosen to be 0.8S/m and target conductivity is 0.6S/m. The size of the target in terms of radial ratio $r'$ is 0.2 ($r' = r/R$, where $r$ is the radius of the target and $R$ is the radius of the circular model).

The images are obtained before and after adding noise. The spatial resolution of an EIT image also depends on the reconstruction algorithm, however, to analyse the effect of pre-processing, the same reconstruction algorithm is used throughout. In this paper, the One Step Gauss Newton linear algorithm is used throughout for reconstruction due to its fast computation [11]. Non-linear transformation is carried out on the noisy data using the proposed method and compared with the pre-processing technique that uses roots of the measured data.

![Figure 2. Reconstructed images – 1st column: Without added noise, 2nd column: with added noise, 3rd column: taking the square root of the noisy data, 4th column: taking the logarithm of the noisy data.](image)

As shown in Figure 2, the targets kept towards the centre in the presence of noise are not detectable because of the low sensitivity towards the centre. Taking the square root and logarithm of the noisy data improves the images, with logarithmic transformation showing even better results.

An EIT system is developed and phantom experiments are carried out as explained in the next section. Image analysing parameters such as Resolution (RES), Contrast to Noise Ratio (CNR) and Position Error (PE) are calculated for quantitative assessment of the images [12,13].

Resolution (RES): This is defined as the ratio of the Area (in pixels) of the reconstructed image on the region of interest (ROI) to that of the total area of the entire reconstructed medium. ROI is defined as the one-fourth amplitude set [12]. The smaller the value of RES, the better the spatial resolution is.

Position Error (PE): This is defined as the difference between the reconstructed image center and the original position of the target. It should be closer to zero.

Contrast to Noise Ratio (CNR): This is defined as the ratio of the difference between the average inhomogeneity conductivity in the ROI and the average background conductivity to that of the
weighted average of the standard deviations of the conductivities in the inhomogeneity region and the background region [13]. The higher the CNR, the better the contrast recovery is.

4.2. Phantom Experiments
A circular tank made of plastic, 20cm in diameter is filled with saline solution. Experiments are carried out by introducing a plastic cylinder, with a radius of 1cm, at different positions in the tank. Images are reconstructed using the Tikhonov algorithm regularized by Maximum a posteriori (MAP) and the effect of root transformations and logarithmic transformation is analysed with respect to the position of the target for different regularization parameters (λ), which is one of the major factors affecting the image reconstruction [14]. The amount of regularization stabilizes the solution at the cost of smoothening of the image [15].

![Position 1](image1.png) ![Position 2](image2.png) ![Position 3](image3.png)

**Figure 3.** Reconstructed images before and after square root and logarithmic transformation for different positions as the amount of regularization is increased.

Figure 3 shows the reconstructed images before and after transformations of the boundary voltages for targets kept at three different positions. It also shows the relative size of the data before and after transformations and it is observed that log transformation shows a considerable increase in the relative size of the data. Logarithmic transformation shows improved images, even for a small amount of regularization, especially for the targets kept away from the electrodes. However, when the target is moved towards the electrodes, the reconstructed image shows a shift in the position of the target as shown in Figure 3 for position 3. Reconstructed images are analysed quantitatively keeping the regularization parameter constant at (λ = 0.1) as the target moves from the centre to the surface.

The plots in Figure 4 show the variation in Resolution (RES), Contrast to Noise ratio (CNR) and Position Error (PE) before and after square root and logarithmic transformations as the target moves closer to the electrodes. Position of the target is defined in terms of radius fraction as the ratio of target radius to that of the circular phantom radius.
Figure 4. Plots showing variation in Resolution (RES), Contrast to Noise Ratio (CNR) and Position Error (PE) before and after square root and logarithmic transformations.

According to Figure 4, logarithmic transformation improves the spatial resolution irrespective of the position of the anomaly, however, it reduces the contrast to noise ratio for targets kept at a distance greater than 60% of the radius from the centre. It also increases position error.

5. Conclusion
In this paper, a pre-processing method based on logarithmic transformation is proposed and compared with the pre-processing technique based on root transformations. EIT shows highest sensitivity towards the electrodes and hence produces good resolution images for anomalies towards the surface electrodes without any non-linear transformations. It is observed that log transformation increases the difference between the boundary voltages, thereby making them distinguishable enough for high resolution imaging. There is a considerable improvement in resolution and contrast to noise ratio after logarithmic transformation for anomalies away from the surface electrodes. One of the limitations of log transformation is that it increases position error especially for anomalies towards the surface.

It is more beneficial to use log transformation when anomalies are away from the surface electrodes i.e. kept at a distance greater than 40% of the radius from the surface electrodes.

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