Comparison of Algebraic Reconstruction Technique Methods and Generative Adversarial Network in Image Reconstruction of Magnetic Induction Tomography (MIT)

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Abstract. Magnetic induction tomography (MIT) is a technique used for imaging electromagnetic properties of objects using eddy current effects. The non-linear characteristics had led to more difficulties with its solution especially in dealing with low conductivity imaging materials such as biological tissues. Two methods that could be applied for MIT image processing which is the Generative Adversarial Network (GAN) and the Algebraic Reconstruction Technique (ART). ART is widely used in the industry due to its ability to improve the quality of the reconstructed image at a high scanning speed. GAN is an intelligent method which would be able to carry out the training process. In the GAN method, the MIT principle is used to find the optimum global conductivity distribution and it is described as a training process and later, reconstructed by a generator. The output is an approximate reconstruction of the distribution's internal conductivity image. Then, the results were compared with the previous traditional algorithm, namely the regularization algorithm of BPNN and Tikhonov Regularization method. It turned out that GAN had able to adjust the non-linear relationship between input and output. GAN was also able to solve non-linear problems that cannot be solved in the previous traditional algorithms, namely Back Propagation Neural Network (BPNN) and Tikhonov Regularization method. There are several other intelligent algorithms such as CNN (Convolution Neural Network) and K-NN (K-Nearest Neighbor), but such algorithms have not been able to produce the expected image quality. Thus,
further study is still needed for the improvement of the image quality. The expected result in this study is the comparison of these two techniques, namely ART and GAN to get the best results on the image reconstruction using MIT. Thus, it is shown that GAN is a better candidate for this purpose.

1. Introduction
Magnetic Induction Tomography (MIT) is an imaging modality which is non-invasive, non-intrusive, robust, electrodeless and apply non-ionizing principle. MIT system which has become the interest in both industrial and medical fields, consists of sensors, signal conditioning circuit and image reconstruction algorithm. Image reconstruction algorithms is the final and very important part of an MIT system. Since MIT was introduced, many algorithms have been proposed for image quality improvement. In general, it is divided into traditional and smart algorithms. Many methods have been introduced previously such as The Gauss-Newton [1], Landweber Iteration [2], Conjugate Gradient (CG) [3] and Tikhonov Regularization method.

Traditional algorithms had been further improved due to their shortcomings. Some examples include Han Min et al. [4] which proposed an algorithm based on weighted matrix and L1 norm regularization to reduce unstable Novel Reconstruction Algorithm (NR). In 2017, Tikhonov proposed a regularized conjugate gradient (CG) algorithm to improve image quality [5]. Then in 2019, Xiao et al. tried to reconstruct a 3D image of a human head model to detect bleeding using Tikhonov regularization and the results were only able to contain limited prior information and to calculate gradients. The objective function takes up a huge amount of memory [6]. Therefore, in this case, it is necessary to conduct an independent trial to produce a good mapping from low to high dimensions.

In the chemical industry, the need for high speed and accurate reconstructed images is also crucial [7][8]. Therefore, smart algorithm is required to meet this expectation. The Algebraic Reconstruction Technique (ART) method is very helpful for this purpose because it can improve the quality of the reconstructed image [9]. Meanwhile, GAN is usually used for image quality improvement in medicine [10] with the technique of extending the object which are the internal part of the human body and this could be observed without having to do surgery such as the reconstruction of the shape or size of the brain tumors [11]. Thus, this involved high accuracy and excellent image quality so this could assist the radiologists to diagnose diseases.

Liu et al. [12] continued the development in 2020 by using multi-stage trained to reconstruct RGB coloring in images. The results are very helpful in terms of solving undetermined problems. The development of the GAN algorithm was also carried out by Yuan et al. [13] to compose images in Magnetic Resonance Imaging (MRI). Chen et al. also used GAN to improve image quality in MIT and the results were good but required a lot of signals detection. Therefore, the purpose of this study is to compare two techniques, namely ART and GAN to get the best results on image reconstruction using MIT.

2. Methodology
2.1. Algebraic Reconstruction Method (ART)
In the ART method, the projection results of each angle would be compared to the original version. If there is a difference, then this is referred to as a correction factor which is later inverted and then used to improve the image quality and this is called an additive ART [14]. Reconstruction diagram of the ART method is shown in Figure 1.
2.2. Generative Adversarial Network Method (GAN)
GAN is a learning machine capable of generating new data with the same statistics as the training set. Where the generator is not only trained to shorten a certain distance in the image but is also used to trick the discriminator. Over-fitting caused by direct feedback can be avoided by solving undetermined and non-linear problems. To build a GAN in this research, it is necessary to train the generator using L2 regularization takes input through phase differences. Later, this had been adapted to the architecture and connected to the discriminator to form a counter network. When the verified generator error is less than 0.05 then the training then be stopped. The overall GAN training process can be referred to Figure 2.

3. Experimental

3.1. Algebraic Reconstruction Method (ART)
In this study, the additive ART method could be simulated using MATLAB. The object used by Fantom Shapp-Logan (Figure 3) is already available in MATLAB. The instruction used to call the file is (equation 1):

$$ A $$

Where A is the phantom. The phantom matrix used is 50 x 50. The angle determines the outcome of the object projection. The weighting matrix (W) is the direction of the x-rays which are parallel beams.
The rotation matrix uses the ‘rotate’ instruction so that it can rotate at $0 – 180$ degrees, with angle intervals of $1, 5, 10, 15, 20$ degrees. Mathematically to get the projection value, this can be written as equation (2):

$$P = W \times A$$

(2)

Where $P$ is projection, $W$ is rotation and $A$ is the weighting matrix. After that, the back projection is done by multiplying the transpose of the weighting matrix with the projection matrix so that it can be written mathematically as equation (3):

$$A = W^T \times P$$

(3)

The results show that the ART mode generates many artifacts which are resulted from back projection. The angle used in the ART method is also very influential on the image quality. The results of the reconstruction of additive and multiplicative using ART method are shown in Figure 4:

**Figure 3**: Phantom Shepp –Logan [14]
3.2. Generative Adversarial Network Method (GAN)

In this section, an 8-channel MIT measurement model was created with an anomaly with a circular range with 8 coils around it. Then, the excitation current is applied to one of the coils and then extracted for the other detection coil. The model can be seen in Figure 5:

![Figure 5](image)

**Figure 5**: Acquisition model of 8 channel MIT [2]

The cylinder in the model is set to represent the measured target with a height and radius of 0.1 m which is also the imaging radius. 8 identical coils with a radius of 0.025 m are mounted on a circular surface at a distance of 0.11 from the centre of the grid. Coils were numbered sequentially in a counter clockwise direction from coils 1 – 8. The anomaly conductivity was 0.05 s/m and this is chosen to simulate the hematoma characteristics and the cylinder model is 0.25 s/m which simulates the electrical characteristics of a normal network. An alternating current with an average of the square root of 1 A and a frequency of 20 Mhz is given to 8 coils. At the same time, conductivity values with the same interval distribution can be extracted as a standard for evaluating post-reconstruction values.

The next stage is to prepare the dataset to train the generator to get results that are under the test. Datasets are widely used to generate samples with random parameters so that it could be used as a database that can train generators to get more accurate results. The next stage is the reconstruction training where this is obtained by dividing the data set into 2 parts which are training and testing. Thus, it minimizes the losses and the generator structure of the proposed GAN based on the data set is {56 128 256 512 1024 2048 4096}. The activation function of the first four layers is ReLU, the fifth to seventh layers are tanh, and the last layer is sigmoid to satisfy the classification output between 0 and 1. Activation function of GAN diagram is shown in Figure 6:
4. Conclusion
From the test results, it can be summarized that the higher the noise level, the worse the reconstruction would be. Then, the GAN can filter out as much noise as possible and filter it out to avoid mapping it to the image. Thus, it is very good to reconstruct the image in MIT. Meanwhile, the ART method is very influential on the angle interval used where the smaller the angle, the better the image quality is going to be. Therefore, GAN is very helpful to solve the inverse problem, thus, it is concluded that the algorithm is potential for MIT imaging reconstruction in comparison to the ART method.

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