3D Digital Breast Tomosynthesis Image Reconstruction Using Anisotropic Total Variation Minimization

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***Abstract*— This paper presents a compressed sensing based reconstruction method for 3D digital breast tomosynthesis (DBT) imaging. Algebraic reconstruction technique (ART) has been in use in DBT imaging by minimizing the isotropic total variation (TV) of the reconstructed image. The resolution in DBT differs in sagittal and axial directions which should be encountered during the TV minimization. In this study we develop a 3D anisotropic TV (ATV) minimization by considering the different resolutions in different directions. A customized 3D Shepp-logan phantom was generated to mimic a real DBT image by considering the overlapping tissue and directional resolution issues. Results of the ART, ART+3D TV and ART+3D ATV are compared using structural similarity (SSIM) diagram.**

I. INTRODUCTION

Digital breast tomosynthesis (DBT) is a new modality that combines the use of tomography and 3D reconstruction with alive organ imaging to provide 3D images of the patient's breast using the small number of low-dose X-ray projections over a limited angular range [1,2]. Due to the limited scan angle, the problem of streaking and blurring artifacts happen during the reconstruction of 3D images [3]. A number of different algorithms have been addressed the problem of reconstructing the images by minimizing the artifacts.

Algebraic reconstruction technique (ART) which was developed by S. Kaczmarz in 1937 has been in use in reconstruction problems [4]. Recently in 2006, D. L. Donoho proved that a sparse image can be reconstructed from an under sampled data set via ℓ_1-norm total variation (TV) method and proposed the compressed sensing (CS) reconstruction algorithm [5]. Later in 2007 Sidky et al. proposed total p-variation (T_pV), which benefits isotropic TV for 2D image reconstruction and developed the same method for 3D objects in 2008 [6,7]. Suggesting that isotropic TV minimization method is unfit for limited-angle CT, Z. Chen et al. introduced 2D anisotropic TV minimization for limited-angle CT reconstruction in 2013 [8].

In this study we introduce 3D anisotropic total variation (3D ATV) method for DBT imaging. Reconstructed image by ART is regularized with a 3D ATV minimization method. It is suggested that the proposed reconstruction method will help in obtaining improved results comparing to conventional methods due to the different resolution in axial and sagittal directions of real DBT imaging. For the simulations 3D Shepp-logan phantom is customized to mimic the resolution difference in axial and sagital directions and the overlapping tissue problem of the real DBT imaging.

In this paper we briefly describe the conventional reconstruction methods and then introduce our newly proposed reconstruction method in Section II, then in Section III the results of comparing the proposed method with conventional techniques are shown after introducing the customized Shepp-logan phantom. Finally, we conclude the study in Section IV.

II. METHODS

A. Algebraic Reconstruction Technique (ART)

ART was one of the iterative reconstruction techniques proposed by Kaczmarz in 1937 [4] and was independently used by Gordon et al. in image reconstruction [9]. Let y_i be the ray-sum measured with the i^{th} ray, the relationship between the x_j and y_i may be expressed as

$$\sum_{j=1}^{N} a_{ij} x_j = y_i, \tag{1}$$

where $i = 1, 2, ..., M, j = 1, 2, ..., N$, a_{ij} is the weighting parameter which stands for the influence of j^{th} cell on the i^{th} ray line integral, x_j is the constant intensity value of the j^{th} cell, M is the total number of rays and N represents the total number of voxels. Iterative methods are introduced for large values of N and M where the conventional matrix inversion methods are not efficient to be used. Finding the solution via subsequent projections is known as the Kaczmarz method which forms the basis of ART.

The implementation procedure starts with an initial guess, $\vec{x}^{(0)}$ which yields in finding $\vec{x}^{(1)}$ and the next iterations continue to find $\vec{x}_j^{(i+1)}$ using $\vec{x}_j^{(i)}$ with the formulated update procedure below in Equation (2),

$$x_j{}^{(i+1)} = x_j{}^{(i)} + \frac{y_i - \sum\limits_{k=1}^{N} a_{ik} x_k{}^{(i)}}{\sum\limits_{k=1}^{N} a_{ik}} a_{ij}, \tag{2}$$

where $i = 1, 2, ..., M, j = 1, 2, ..., N$. This process is repeated untill all projections are considered and all pixel values converge to a solution [9, 10, 11].

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B. Compressed Sensing (CS)

Compressed Sensing (CS) image reconstruction is used to reconstruct a sparse image by minimizing the ℓ_1-norm of the sparse image. The image can be sparsified using a sparsifying transform (ψ) which is a linear transform operator and is used to transform a non-sparse image to a sparse form. CS theory tries to solve a constrained minimization problem given in (3):

$$min\|\psi X\|_1, s.t. AX = Y. \tag{3}$$

Equation (3) can be implemented by minimizing TV of the reconstructed image by the ART algorithm in DBT imaging problem. 3D TV of X can be given as,

$$TV_{3D}(X_{i,j,k}) = \sum_{i,j,k=1}^{N} | \bigtriangledown_{i,j,k} (X_{i,j,k})|_1, \tag{4}$$

where the discrete gradient, $\bigtriangledown_{i,j,k}(X_{i,j,k})$, in (4), is shown as:

$$| \bigtriangledown_{i,j,k} (X_{i,j,k})| = \sqrt{(D_x X)^2 + (D_y X)^2 + (D_z X)^2}, \tag{5}$$

where $X_{i,j,k}$ is the intensity value at voxel $(i, j, k), D_x X = X_{i,j,k} - X_{i+1,j,k}, D_y X = X_{i,j,k} - X_{i,j+1,k}$ and $D_z X = X_{i,j,k} - X_{i,j,k+1}$.

C. The Proposed Method: 3D Anisotropic Total Variation Minimization (3D ATV)

Proposed method was developed by adapting the TV term in ART+TV method for the DBT imaging by considering the varying resolution issues in axial and sagittal directions.

The cost function of 3D ATV for DBT imaging problem can be formulated as:

$$C = \sum_m (y_m - \sum_n A_{mn} x_n)^2 + \lambda ATV(x), \tag{6}$$

where x and y represent the image and measured projection vectors respectively, A_{mn} is the projection matrix element from voxel n to detector m and λ is the ATV coefficient where the $ATV(x)$ is defined as follows:,

$$\begin{aligned} ATV(x) = &\sum_i \sum_j \sum_k (\alpha.|x_{i,j,k} - x_{i+1,j,k}|^2 \\ &+ \alpha.|x_{i,j,k} - x_{i,j+1,k}|^2 \\ &+ \beta.|x_{i,j,k} - x_{i,j,k+1}|^2)^{0.5}, \end{aligned} \tag{7}$$

where α and β are the key parameters of the proposed method controlling anisotropic resolution matter of DBT imaging. In DBT imaging, sagittal resolution is 100 μm^2 while axial resolution is $1mm^2$. Therefore $\alpha = 10\beta$ is chosen in our study. The position relationship of voxel $X_{i,j,k}$ and other voxels located in its neighborhood is shown in Figure 1.

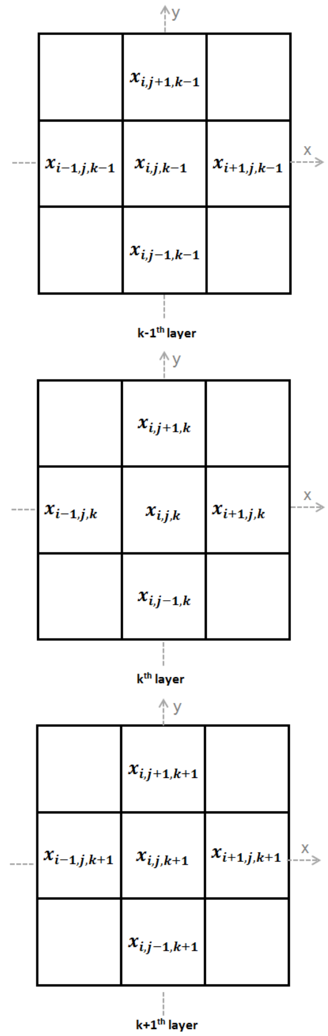


Fig. 1. Voxel $x_{i,j,k}$ and its neighbourhood voxels

III. RESULTS

In order to investigate the performance of different reconstruction methods, a 3D shepp-logan phantom was customized to mimic the difference between sagittal and axial resolutions. The phantom was also modified to imitate the overlapping tissue problem of the DBT imaging. The phantom includes smaller objects with lower X-ray absorption values at lower layers which are obscured by the larger objects with higher X-ray absorption values. Different layers of the customized 3D Shepp-Logan phantom are shown in Figure 2. Parameters of the simulator and phantom are listed in Table I below.

Original layer of interest (LOI) of the phantom and reconstructed images of the LOI by ART, ART+3D TV and ART+3D ATV methods are shown in Figure 3 (a) to (d), respectively.

In order to exhibit the quality comparison of reconstructed methods we utilize one of the well-known quality assessment methods, measure of structural similarity (SSIM), which is used to compare the local patterns of pixel values which are

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Source to Detector Distance	300 pixels
Object to Detector Distance	100 pixels
Phantom Size	$120 \times 120 \times 12$ pixels
Detector Size	$160 \times 160 \times 1$ pixels
Scan Angle	$50°$
Number of Projections	11
Number of Iterations	15

normalized for amount of luminance and contrast [12]. The SSIM index is shown below,

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(\sigma_{xy} + C_2)}{({\mu_x}^2 + {\mu_y}^2 + C_1)({\sigma_x}^2 + {\sigma_y}^2 + C_2)}, \quad (8)$$

where μ_x and μ_y refer to mean of the intensities of signals x and y respectively and σ_x and σ_y are the standard deviation of them. C_m is given below,

$$C_m = K_m L^2, m = 1, 2, \quad (9)$$

where L is the dynamic range of the pixel values and $K_m \ll 1$ for $m = 1, 2$ are small constants. Practically we need a single overall quality measure of the entire image. In this study we used a mean SSIM (MSSIM) index to evaluate the overall image quality.

$$MSSIM(X,Y) = \frac{1}{M}\sum_{j=1}^{T} SSIM(x_j + y_j), \quad (10)$$

where X and Y refer to original and reconstructed images, respectively; x_j and y_j are the image contents at the j^{th}

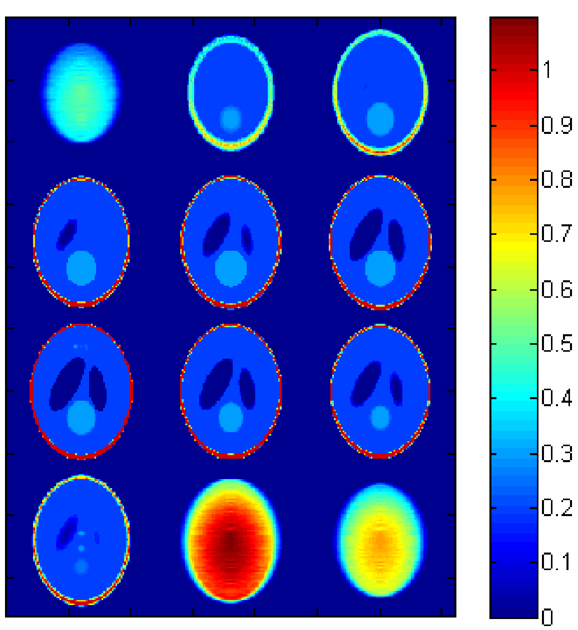
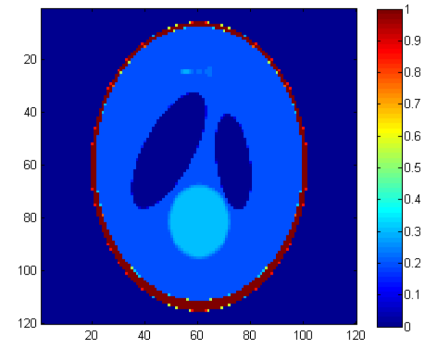
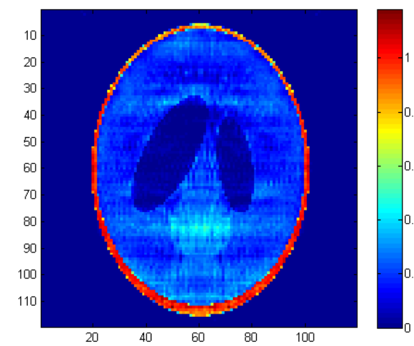


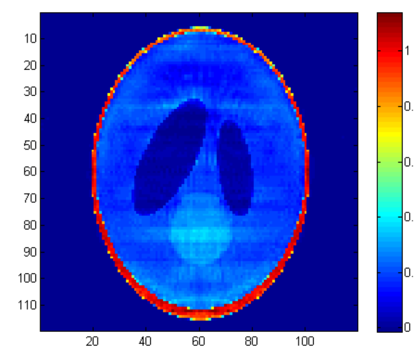
Fig. 2. Layer by layer display of customized 3D Shepp-Logan phantom.



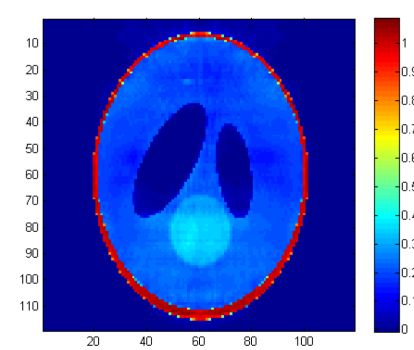
(a)



(b)



(c)



(d)

Fig. 3. (a) Original LOI, (b) LOI after 15th iteration of ART, (c) LOI after 15th iteration of ART + 3D TV, and (d) LOI after 15th iteration of ART + 3D ATV.

local window and T is the number of local windows of the image.

Figure 4 displays mean SSIM (MSSIM) of the reconstruction methods. ART + 3D ATV method provided improved results compared with the result of ART and ART + 3D TV method.

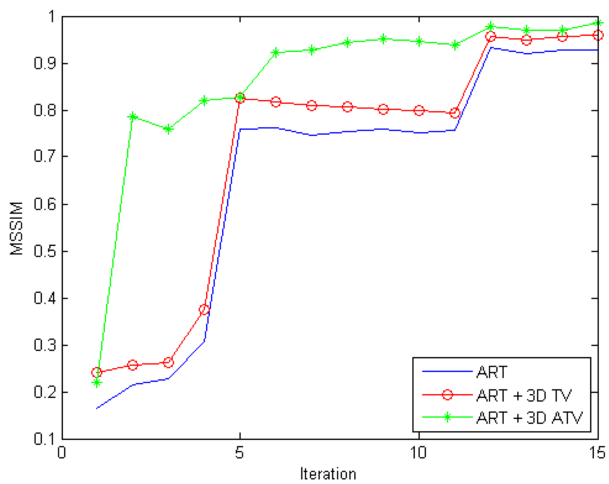


Fig. 4. Comparison of MSSIM for ART, ART + 3D TV, and ART + 3D ATV reconstruction techniques.

As shown in this Figure, the proposed method, ART + 3D ATV, exhibits better image quality comparing to both ART and ART + 3D TV methods in terms of MSSIM index value.

IV. CONCLUSIONS

A 3D DBT image reconstruction method using anisotropic total variation minimization was developed in this study. This method was formulated considering the difference in sagittal and axial directions of DBT imaging. The simulation results carried out in this study suggested that ART+3D ATV method can give better results in DBT imaging problem compared with ART and ART+3D TV methods.

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