Pre-computed backprojection based penalized-likelihood (PPL) reconstruction with an edge-preserved regularizer for stationary Digital Breast Tomosynthesis

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ABSTRACT

Stationary Digital Breast Tomosynthesis (sDBT) is a carbon nanotube based breast imaging device with fast data acquisition and decent projection resolution to provide three dimensional (3-D) volume information. Tomosynthesis 3-D image reconstruction is faced with the challenges of the cone beam geometry and the incomplete and nonsymmetric sampling due to the sparse views and limited view angle. Among all available reconstruction methods, statistical iterative method exhibits particular promising since it relies on an accurate physical and statistical model with prior knowledge. In this paper, we present the application of an edge-preserved regularizer to our previously proposed precomputed backprojection based penalized-likelihood (PPL) reconstruction. By using the edge-preserved regularizer, our experiments show that through tuning several parameters, resolution can be retained while noise is reduced significantly. Compared to other conventional noise reduction techniques in image reconstruction, less resolution is lost in order to gain certain noise reduction, which may benefit the research of low dose tomosynthesis.

Keywords: edge-preserved regularization, non-quadratic penalty, stationary digital breast tomosynthesis, statistical iterative reconstruction, noise reduction.

1. INTRODUCTION

Digital Breast Tomosynthesis (DBT)\textsuperscript{1, 2} draws a lot of attentions in clinical applications to improve early breast cancer detection by providing three dimensional (3-D) anatomical imaging. Currently most DBT systems are built upon the regular full-field digital mammography (FFDM) systems and require partial isocentric motion of an X-ray tube over certain angular range to acquire multiple projection data. This prolongs the scanning time and degrades the imaging quality. To reduce the limitations above, a stationary DBT (s-DBT) scanner has been developed based on the spatially distributed multi-beam field emission X-ray (MBFEX) source technique with the carbon nanotube (CNT)\textsuperscript{3, 4}.

In Tomosynthesis, 3D image reconstruction is faced with challenges of the cone beam geometry and the incomplete and nonsymmetric sampling due to sparse views and limited view angle. These challenges lead to reduced image quality in clinical applications, such as high noise and serious out-of-plane artifacts. Among all available reconstruction method, statistical iterative reconstruction\textsuperscript{5} exhibits particularly promising since it provides the flexibility of accurate physical noise modeling and geometric system description. In our previous study, we proposed pre-computed backprojection based penalized-likelihood (PPL) reconstruction with a quadratic penalty\textsuperscript{6–8} which provides predictable image quality based on a pre-computed look-up table. However, a quadratic penalty has a uniform influence on entire voxels, which may lead to a over-smoothening on edges. The purpose of this paper is to introduce a non-quadratic regularizer to set up a more flexible framework to balance the edge-preservation and noise reduction. The parameter choice of the regularizer is also investigated to gain better image quality based on phantom studies with sDBT system.
2. METHODS AND MATERIALS

In the model of X-ray imaging, the poisson distribution of incident photon number dominates the physical process. Although X-ray detectors are not quanta counters, the signal statistics of mono-energetic X-ray detection is still considered to be a poisson distribution. The probability of photon number detected along the $i$-th X-ray is described mathematically as

$$ P(Y_i = y_i) = \frac{\theta_i^{y_i} e^{-\theta_i}}{y_i!}, $$

where $Y_i$ is a random variable counting the observed photons on the detector along $i$-th X-ray; $y_i$ is the observation of $Y_i$; $\theta_i$ is the expectation value of the random variable $Y_i$. $\theta_i$ can be expressed as

$$ \theta_i = d_i e^{-<\mu,l_i>}, $$

where $d_i$ is the intensity of the incident X-ray beam; $\mu$ is a linear attenuation coefficient vector to be estimated. $l_i$ denotes the vector of the intersection length of the $i$-th X-ray within voxels. The negative log-likelihood function of all observed photons on the detector can be written as

$$ L(\mu) = \sum_i M \{d_i e^{-<\mu,l_i>} + y_i < \mu, l_i > \} + c, $$

where $M$ is the number of X-ray beams; $c$ is a constant.

By applying a $\lambda$-scaled regularizer $R$ to penalize the likelihood function, the noise induced by X-ray scattering and electronic noise can be mitigated. The log penalized-likelihood function can be written as

$$ \Phi(\mu) = L(\mu) + \lambda R(\mu) $$

Previously we introduced a modified quadratic regularizer\cite{6,7} into Tomosynthesis statistical reconstruction to quantify the effect of $\lambda$ on resolution properties,\cite{11} which is

$$ R_m(\mu) = \sum_j N \kappa_j^2 \sum_k (\mu_j - \mu_k)^2, $$

where $N$ is the total number of voxels; $N_j$ denotes the index subset of the neighbour voxels of the $j$-th voxel. $\kappa$ can be computed by a backprojection equivalent operation, which is

$$ \kappa_j^2 = \frac{\sum_i^M l_{ij}^2 y_i}{\sum_i^M l_{ij}^2}. $$

$\kappa$ absorbs the data-dependency term in resolution properties. Thereby a uniform resolution can be achieved within the reconstructed volume.

A quadratic penalty has a uniform influence on universal voxels, which may lead to a over-smoothed edge. The generalized Gaussian Markov random field (GGMRF) as a edge-preserved prior was introduced in literature,\cite{12} A more flexible q-generalized Gaussian MRF (q-GGMRF) was applied in model based iterative reconstruction (MBIR)\cite{13} which offers the potential of combined noise reduction, high spatial resolution, contrast enhancement and artifact reduction for low-dose imaging or enhanced image clarity for improved diagnostic confidence. In our Tomosynthesis application, we use the simpler GGMRF to gain these benefits, which has the form as follows

$$ R_m(\mu) = \sum_j N \kappa_j^2 \sum_k (\mu_j - \mu_k), $$

where

$$ \rho(\Delta) = \left| \frac{\Delta}{c} \right|^p. $$
The corresponding derivative is known as the influence function

$$\rho'(\Delta) = \frac{p|\Delta|^{p-1}}{c^p} \text{sign}(\Delta).$$

(9)

The exponent parameter $p$ of the GGMRF allows one to control the degree of edge preservation in the reconstruction. As long as $p > 1$, the resulting regularizer term is strictly convex. The constant $c$ determines the approximate threshold of transition between low and high contrast regions. When $p = 2$ and $c = 1$ the regularizer term is quadratic and the reconstructed images tend to produce a softer edge. As $p$ is reduced, the regularizer becomes non-quadratic and edge sharpness tends to be preserved.

In Fig. 1, we compare the influence function of the quadratic regularizer to several edge-preserving GGMRF priors. In the quadratic cases ($p = 2$), the influence functions are linear around the origin, which controls textures in a uniform manner. Reduced $p$ retains better edge-preserving characteristics, as influence function tends to be constant for larger difference of voxel. The value $c$ controls the inflexion point. Higher $c$ pushes the edge preserving behaviour towards the origin. For example, to maintain the influence as the same as the quadratic below the difference value of 0.01, which is considered as the upper boundary of noise level, the $c^p$ values for the cases $p = 1.8, p = 1.7, p = 1.6$ are set as 2.5, 3.5, 5.3.

With the choice of the strictly convex regularizer, the objective function defined in Eq. 4 has a unique global minimum. To estimate voxels at the unique global optimum, both ICD\textsuperscript{14} and relaxed OS-SPS\textsuperscript{15} can provide fast algorithms. The former produces a faster convergence on high frequency voxel with a sequential voxel update and the latter provides a parallel computation with a decent convergence rate. We choose relax OS-SPS in our application for a more flexible parallel computing framework. By applying the idea of optimization transfer\textsuperscript{16} on GGMRF regularizer, the iterative solution is derived as follows.

$$(10)$$
backprojection (FBP) and ordered subsets maximum likelihood expectation minimization (OSEM) are presented as well. \( \lambda \) in OS-PPL is preset as 8 according to our previous study.\(^6\) To guarantee global convergence, all iterative methods are initialized by three-time iterations of OS method and followed by a non-OS method for ten-time iterations.

The data was collected with the sDBT prototype system.\(^3,4\) Scatter correction technique\(^17\) is applied with the data to improve the high and low contrast. The origin of the 3-D coordinate system is located at the center of the detector. A flat panel detector is used for image acquisition. With a 140\( \mu \)m pixel pitch, the total image size is 2048x1661. The multiple X-ray beams are positioned along a straight line parallel to the detector plane. The source is designed to have 15 X-ray beams spanning a distance of 32.38cm from end to end. The linear spacing between the X-ray beams varies to provide an even 2\(^o\) angular spacing. A 3-D breast phantom is placed on a stage with a 2.54 cm air gap. The images were acquired using: 28Kv, molybdenum filter, molybdenum target and 20mAs per projections.

3. RESULTS

Fig. 2 and Fig. 3 present mass and micro-calcifications equivalent objects in respective focus plane reconstructed by OS-PPL with our proposed regularizer and other representative algorithms. In Fig. 2, one can see that statistical iterative methods provide better artifacts suppression around objects than FBP. In addition, the OS-PPL with \( p = 1.8, c^p = 2 \) presents best noise reduction among all investigated methods. In Fig. 3, the micro-calcifications can be clearly seen with statistical iterative methods, while FBP yields a little blurred sharpness along horizontal direction.

Point spread function (PSF) curves in Fig. 4 are measured by crossing the isolated micro-calcification in Fig. 3. These PSF curves are then fitted into the Gaussian functions to remove the noise. The Fourier transform of the fitted Gaussian function is the MTF. The resolution frequency at 50\% MTF peak value was used as the quantitative measure of the in-plane image resolution. As shown in Fig. 5, OSEM and OS-PPL with \( p = 1.8, c = 2.5 \) provide more precise resolution than other methods. The resolution produced by quadratic OS-PPL is similar to FBP. Contrast to noise ratio is used to present the capability of low contrast detection. In our experiments, CNR are evaluated by subtracting the mean value in the background from the mean value in the mass shown in Fig. 2 and dividing the standard deviation in the background. The half width of 50\% MTF, standard deviation and CNR are summarized in Tab. 1.
0.00077  12.3928  4.0223
0.0014  6.6576  4.7755
0.0015  6.2315  4.2981
0.0571  2.7160  4.2255

According to Tab. 1, OSEM provides the best resolution but a little lower CNR. OS-PPL with $p = 1.8, c = 2$ presents a superior CNR among all which is almost improved by 5-fold compared to FBP. However, the regularizer with $p = 1.8, c = 2$ tends to soften the sharpness of micro-calcification. Overall, the regularizer with $p = 1.8, c = 2.5$ produces a comparable resolution to OSEM and a decent CNR which is 1.5 times better than OSEM and 2.5 times better than FBP.

4. CONCLUSION

Statistical iterative reconstruction exhibits particular promising since it provides the flexibility of accurate physical noise modeling and geometric system description in transmission imaging system. In our previous study, OS-PPL reconstruction with a quadratic penalty was proposed to provide predictable image quality of reconstructed results, where the tradeoff between resolution and noise can be controlled by adjusting the scalar $\lambda$ based on a pre-computed look-up table. In this study, to reduce the noise without significant resolution loss, an edge-preserved regularizer was proposed to our OS-PPL method with a sDBT system. Two extra parameters are introduced to make tuning image quality more flexible and achievable. Influence function is presented to visualize the effect of these parameters on resolution. Experiment results show that by the proposed regularizer, resolution can be retained as much as possible while noise is reduced by tuning the parameter $p$ and $c$. This benefit may allow to reduce the X-ray dose while maintaining a comparable image quality. Further experiments are needed to seek an optimal parameter combination. In addition, dose reduction experiments will be conducted with the inspiration of the edge-preserved iterative technique.

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REFERENCES


