Performance comparison of OS–EM algorithm with ML–EM in Digital Tomosynthesis

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Abstract— **Recently digital tomosynthesis (DTS) is under active research for clinical applications including diagnosis and interventional imaging. Image reconstruction algorithm is important in DTS, beacuse the scanning angle is limited and the data are insufficient for volumetric imaging. Many iterative algorithms have been proposed for DTS in addition to the conventional analytic algorithms. Maximum–likelihood expectation–maximization(ML–EM) algorithm is one of the popularly used algorithms for emission tomography, and ordered–subset expectation–maximization(OS–EM) algorithm has been proposed to speed up the reconstruction without sacrificing image quality. To our knowlege, however, there has been no report on the utility of OS–EM algorithm in comparison with the ML–EM for DTS. In this paper, we demonstrate that the OS–EM algorithm can produce images with higher quality than those reconstructed by the ML–EM algorithm under a constraint of given reconstruction time. We used an XCAT phantom for performance comparison of ML–EM and OS–EM algorithm in DTS. To evaluate the image quality, we used a detectability of a prewhitening observer.**

Keywords— **ML–EM algorithm, OS–EM algorithm, Digital Tomosynthesis**

I. INTRODUCTION

Digital tomosynthesis (DTS) has recently been reinvigorated for its clinical utility in diagnostics and interventional imaging along the progress in imaging technologies with an emphasis on low-dose. Digital breast tomosynthesis and digital chest tomosynthesis provide multiple slice images of a patient which usually help enhance the visibility of tumors compared to mammography or radiography. DTS uses a limited-angle data. While it does not have a good depth resolution [1, 2], its in-plane resolution is in general acceptable for clinical purposes.

Image reconstruction algorithm plays an important role in DTS, beacuse the scanning angle is limited and the data are insufficient for volumetric imaging. Many iterative algorithms have been proposed for DTS in addition to the conventional analytic algorithms such as backprojection, filtered-backprojection, or backprojection-filtration algorithms. Maximum–likelihood expectation–maximization(ML–EM) algorithm [3] is one of the popularly used iterative algorithms particularly for emission tomography [4], and ordered–subset expectation–maximization(OS–EM) algorithm [5] has been proposed to speed up the reconstruction without a noticeable loss in image quality.

The success of OS–EM is partly due to the (quasi-)orthogonality of the data of a subset selected for a single iteration. We were interested in the performance of OS–EM in comparison with ML–EM under a constraint of reconstruction time in DTS. Since the available data in DTS are limited in terms of scanning angle, the orthogonality of the data is thought to be weaker than other tomographic imaging modalities. We used an XCAT phantom for performance comparison of ML–EM and OS–EM algorithm in DTS. To evaluate the image quality, we used a detectability of a prewhitening observer.

II. MATERIALS AND METHODS

We simulated a digital chest tomosynthesis using an XCAT phantom. The scanning parameters used in the simulation are as follow: R=100cm, D=150cm, scan-angle=60°. We acquired 15 views evenly distributed over the scanning range. In the OS–EM algorithm, each subset contains 5 views equally spaced. For computation, we used a single CPU in this work.

A. Reconstruction Algorithm

For image reconstruction of DTS, we ued the ML–EM and OS–EM algorithms. The update formula in each iteration of ML–EM algorithm can be written as [6]

$$f^{k+1} = f^k \mathbf{A}^T \frac{g}{\mathbf{A} f^k} \quad k = 0, 1, \ldots \tag{1}$$

, where $\mathbf{A}$ is a system matrix of projection, f refers to the reconstructed image, and g represents the data.

The OS–EM algorithm is similiar to the ML–EM algorithm. But, it uses subsets in each iteration. At each updating time, a subset of the projection data is used.

$$\begin{aligned} f^{k,0} &= f^{k}, \\ f^{k,j} &= f^{k,j-1}\frac{1}{a}\mathbf{A}_j^T\frac{g_j}{\mathbf{A}_j f^{k,j-1}} \quad j=1,\ldots,\text{subset}, \\ f^{k+1} &= f^{k,p} \end{aligned} \tag{2}$$

The update formula of the OS–EM algorithm is shown above and $a = \mathbf{A}_j^T \mathbf{1}$ is independent of j.

We also hybridized the ML–EM and OS–EM algorithms to see if there is any significant effect in DTS reconstruction. One possible hybrid OS–EM algorithm can read as

$$\begin{aligned} f^{k+1} &= f^{k}\mathbf{A}^T\frac{g}{\mathbf{A}f^{k}} \quad k=0 \\ f^{k,0} &= f^{k+1}, \\ f^{k,j} &= f^{k,j-1}\frac{1}{a}\mathbf{A}_j^T\frac{g_j}{\mathbf{A}_j f^{k,j-1}} \quad j=1,\ldots,\text{subset}, \\ f^{k+1} &= f^{k,p}. \end{aligned} \tag{3}$$

B. Detectability

We evaluated image quality using a prewhitening(PW) observer of a reconstructed lung nodule in the XCAT phantom. We used detectability of a signal in complex backgrounds [7]. The detectability square is defined as following [8]

$$d'^2 = \sum_{\mathbf{k}} \frac{|\mathrm{S}(\mathbf{k})|^2}{\mathrm{P}_c(\mathbf{k})}, \tag{4}$$

where $\mathrm{S}(\mathbf{k})$ is Fourier transform of mass signal, $\mathrm{P}_c(\mathbf{K})$ is the noise power spectrum acquired from the background.

$$\mathrm{P}_c(\mathbf{k}) = \frac{1}{\mathrm{L}} \sum_{l=1}^{L} |\mathrm{DFT}\{\mathbf{W}(\mathbf{f}_l - \mathbf{f}_{ave})\}|^2, \tag{5}$$

where $\mathbf{f}_l$ is the l^{th} ROI of image, $\mathbf{f}_{ave}$ is the mean ROI image, and $\mathbf{W}$ is a Hann window.

III. Results

We fixed the total computation time as a constraint, and compared the detectability of images reconstructed by each algorithm. Figure 1 shows the slice images that contain a lung nodule reconstructed by each algorithm, and Figure 2 shows the computation time of each algorithm as a function of iteration number, and it also shows the detectability of a lung nodule in the reconstructed images. For a given computation time limit, OS–EM algorithm runs more iterations than the ML–EM algorithm. The detectability of the OS–EM reconstructed image is higher than that of the ML–EM image, and Hybrid OS–EM image has a little lower detectability than that of the OS–EM image.

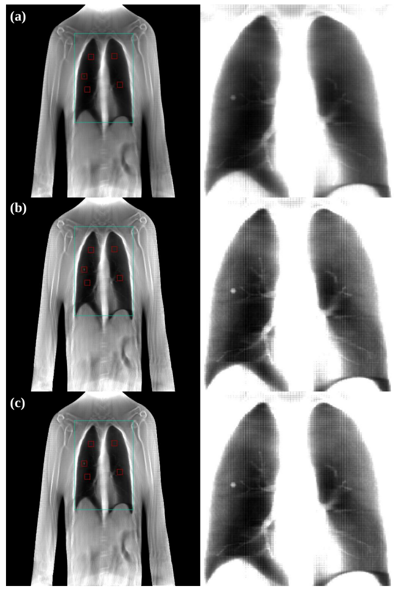

Fig. 1: Result of each algorithm image is shown in (a). ML-EM algorithm(Number of iteration is 16), (b). OS-EM algorithm(Number of iteration is 29) and (c). Hybrid OS–EM algorithm(Number of iteration is 28).

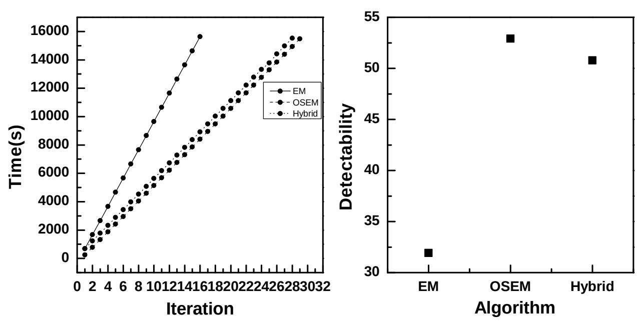

Fig. 2: Time of each iateration and detectability of each algorithm

We then fixed the number of iterations, and compared the detectability of images reconstructed by each algorithm. Figure 3 shows the reconstruction images at the 16^th iteration by each algorithm. Figure 4 shows the computation time of each algorithm, and also shows the detectability of the reconstructed images. The detectability results are similar to the previous case; OS–EM algorithm produces slightly higher detectability than ML–EM algorithm. Note that the detectability axis is in a different scale than in Fig. 2.

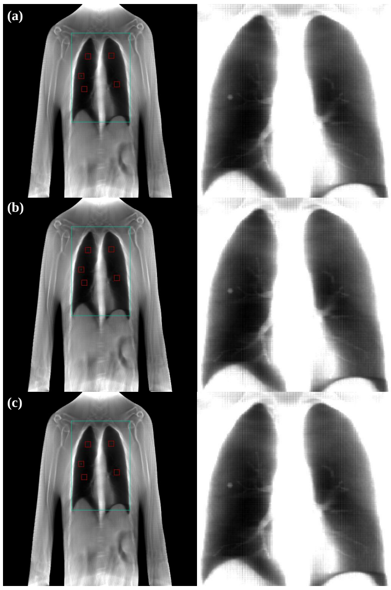

Fig. 3: Result of each algorithm image is shown in (a). ML-EM algorithm, (b). OS-EM algorithm and (c). Hybrid OS–EM algorithm.

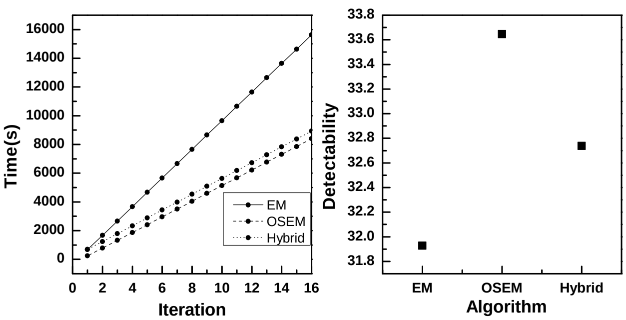

Fig. 4: Time of each iateration and detectability of each algorithm

Figure 5 shows the detectability as a function of iteration by each algorithm. As the number of iteration increases, OS–EM algorithm and the Hybrid OS–EM algorithm show a similiar increase in detectability. The detectability in the reconstructed image by the ML–EM algorithm appears to increase more slowly than that by the OS–EM.

IV. Conclusion

We have conducted a performance compaison study on ML–EM and OS–EM algorithms for DTS image reconstruction. In our study, the OS–EM algorithm produced images of higher detectability than the ML–EM algorithm under a constraint of computation time or iteration number. Although the orthogonality data condition in emission tomography does not exactly exist in DTS, our results suggest that it is an appropriate approximation. Moreover, the OS–EM provides an efficient way of image reconstruction under a constraint of computation time.

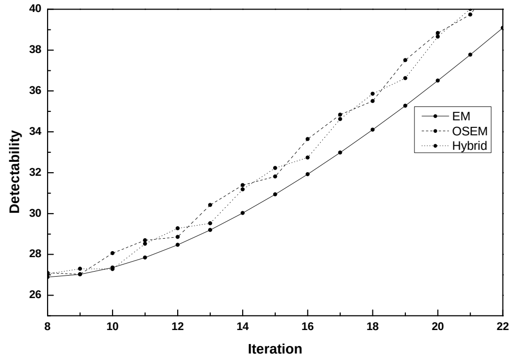

Fig. 5: Detectability of each iteration

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