Preliminary attempt on maximum likelihood tomosynthesis reconstruction of DEI data*

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Abstract Tomosynthesis is a three-dimension reconstruction method that can remove the effect of superimposition with limited angle projections. It is especially promising in mammography where radiation dose is concerned. In this paper, we propose a maximum likelihood tomosynthesis reconstruction algorithm (ML-TS) on the apparent absorption data of diffraction enhanced imaging (DEI). The motivation of this contribution is to develop a tomosynthesis algorithm in low-dose or noisy circumstances and make DEI get closer to clinic application. The theoretical statistical models of DEI data in physics are analyzed and the proposed algorithm is validated with the experimental data at the Beijing Synchrotron Radiation Facility (BSRF). The results of ML-TS have better contrast compared with the well known 'shift-and-add' algorithm and FBP algorithm.

Key words diffraction enhanced imaging, maximum likelihood reconstruction, tomosynthesis

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1 Introduction

Tomosynthesis is a limited-angle tomography method which allows reconstruction of three-dimension objects from a limited number of angular views. As the technique of high-resolution and large scale flat-panel detector develops, more attention has been paid to tomosynthesis these years especially in the medical imaging field where radiation dose is concerned, e.g. mammography, chest imaging, and orthopedic imaging[1]. Compared with computer tomography (CT), tomosynthesis has irreplaceable superiority in radiation dose control and inspection time saving. The basic idea of tomosynthesis was first presented by Ziedses des Plantes[2] who used a simple "shift-and-add" principle. Grant[3] showed a proof of concept and coined the term "tomosynthesis" in 1972. A comprehensive review of tomosynthesis techniques was given by Dobbins et al[1]. Tomosynthesis reconstruction algorithms can be divided into three categories[4—6]: the 'shift-and-add' algorithm, which is also named back projection (BP), the filtered back projection type algorithms (FBP), and the iterative algorithm. The BP algorithm is simple and fast, but suffers structural artifacts; the efficiency of FBP type algorithms depends on the filter design; the iterative algorithms including ART and statistical iterative algorithms perform the reconstruction in a recursive fashion and have advantages in noise suppression when data are not sufficient.

X-ray diffraction enhanced imaging (DEI) has been a hot field after the first system was developed by Chapman et al in 1996[6]. It has extremely high sensitivity for weakly absorbing low-Z samples and can reveal elaborate details of medical and biological tissues. Recently tomosynthesis based on DEI was studied. Maksimenko et al showed the results of tomosynthesis based on the refraction angle data of DEI with a 'shift-and-add' algorithm[7]. His results show that tomosynthesis based on DEI is promising because of the high sensitivity to the soft tissue contrast and the extremely low radiation dose.

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Although DEI is mainly implemented on synchrotron radiation, the translation of the system to a conventional X-ray source is also practicable. The recent experiments[8, 9] prove the possibility of DEI method for clinic application. In this paper, a maximum likelihood tomosynthesis algorithm (ML-TS) is proposed to reconstruct slices of DEI data. The theoretical statistical models of DEI projection data, especially the apparent absorption data[6], are analyzed. The motivation of adopting statistical algorithms is to gain acceptable tomosynthesis reconstruction in low-dose or noisy circumstances where short inspection time is expected or radiation dose on patients is concerned. Successful tomosynthesis reconstruction in these circumstances can make the DEI method get closer to clinical application, such as applications in mammography.

2 Method

The layout of the DEI system is shown in Fig. 1 of Ref. [10]. X-rays from synchrotron radiation (or X-ray tube) first irradiate on a single perfect crystal which acts as the monochromator to produce a quasi-parallel beam of monochromatic X-rays. After propagating through the sample, the beam is diffracted by another perfect crystal which acts as the analyzer. Several images are taken at different positions of the Rocking Curve (RC). The signal detected by the detector contains absorption, refraction and scattering information, thus absorption contrast, refraction contrast or scattering contrast can be generated from the DEI data.

Tomosynthesis in DEI is consistent with the original DEI system, and it can be implemented without modifying the configuration. The scheme of the tomosynthetic sampling is shown in Fig. 1. For simplicity, only the sampling of a two-dimensional slice paralleling to X-Y plane is illuminated.

The sampling is parallel with equal space in the DEI system. According to the central slice theorem[11], the sampling points are at a portion of a concentric circle along the radial direction in the Fourier domain. It can be seen in Fig. 1(b) that the sampling along the direction of the spatial frequency f_Y is missing more than that along the direction of f_X, thus the spatial resolution of the reconstructed image along the X direction is higher than that along the Y direction. The target of tomosynthesis is to reconstruct slices that parallel to X-Z plane in Fig. 1 of Ref. [10].

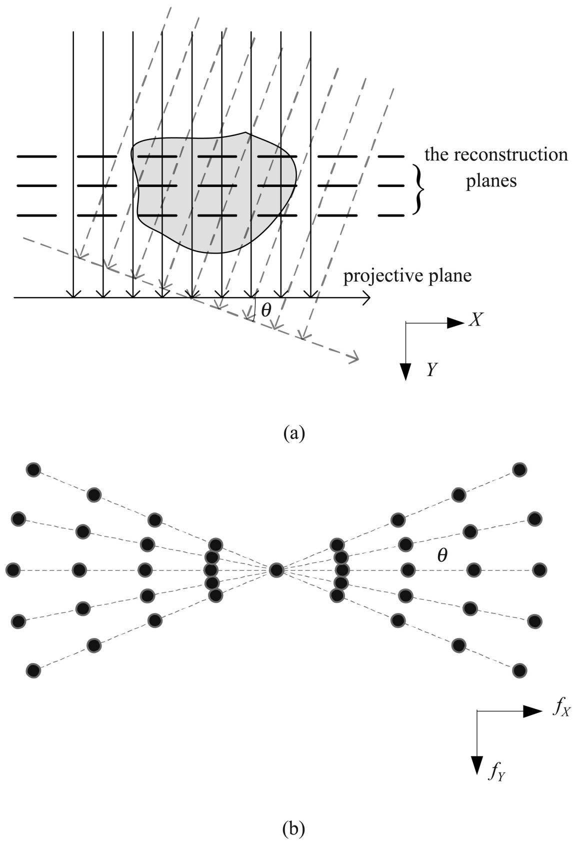

Fig. 1. Tomosynthetic sampling. (a) Schematic illustrations tomosynthesis acquisition; (b) Sampling in Fourier domain of the tomosynthesis acquisition, f_X and f_Y are the spatial frequency along the X and Y direction, respectively.

To adopt the maximum likelihood method in the tomosynthesis reconstruction, first, a statistical model in physics should be created. In the field of emission and (monoenergetic) transmission CT, the Poisson statistical model is well known and widely used[12]. For emission CT, the Poisson model is natural when the law of radioactive decay of substance is considered. For transmission CT, Poisson model is adopted from the view of noise of detection rather than the law of radioactive decay. In our experiment, a flat Charge Coupled Device (CCD) detector with numerous pixels was adopted and transmission projections at several different angles were measured. Each pixel receives a ray at each projection. The transmission measurement of each ray is assumed to follow a Poisson distribution[12]:

$$y_i \sim \text{Poisson}\{b_i \mathrm{e}^{-[Ax]_i} + r_i\} \tag{1}$$

where y_i denotes the transmission measurement of the ith ray, b_i denotes the blank scan (without sample) measurement of the ith ray, and r_i denotes the mean number of background counts. $[Ax]_i=\sum_j^N a_{ij}x_j$ $(j=1,2,\cdots,N)$ represents the ith ray integral of the attenuation map in which x_j is the unknown attenuation coefficient in the jth pixel, $A=\{a_{ij}\}$ is the system matrix, and a_{ij} is the weighting factor that represents the contribution of the jth pixel to the ith ray integral, and N is the number of pixels. In practice, $\{b_i\}$, $\{a_{ij}\}$, $\{r_i\}$ are known nonnegative constants.

The Poisson statistical model is not strictly true if the scattering exists and the X-ray is not monochromatic. These situations are usually not fulfilled in transmission X-ray systems. As to DEI data, the apparent absorption data can be presented in the form of[6]:

$$I_{\text{abs}}=I_0\exp\left\{-\int_l(\mu+\chi)\mathrm{d}l\right\} \tag{2}$$

where μ and χ are the absorption and the extinction coefficients, respectively.

The apparent absorption data can be thought as pure absorption and extinction information without the scattering[6], meanwhile because the X-ray beams in DEI are (almost) monochromatic, a Poisson statistical model is more accurate for apparent absorption data of DEI than those from the transmission X-ray systems.

In this paper, as a preliminary study, we focus on the apparent absorption data of DEI. In terms of the refraction-angle data there isn't a proper model to depict them until now. For the scattering data, a normal distribution may be feasible which has been adopted in the field of cosmic ray muon radiography[13].

To implement a maximum likelihood tomosynthesis reconstruction of the DEI data, there are two strategies. Since the beams of DEI are parallel, the reconstruction could be performed slice by slice along the Z direction in Fig. 1 of Ref. [10] and finally slices are formed in the X-Z plane, or performed in a direct 3D reconstruction. However, the former strategy is more time-saving and memory-saving when implemented by computer and is adopted in this paper.

The log-likelihood function of maximum likelihood tomosynthesis algorithm is[14, 15]

$$L(x)=\sum_i h_i([Ax]_i) \tag{3}$$

where

$$h_i(l)=y_i\log(b_i\mathrm{e}^{-l}+r_i)-(b_i\mathrm{e}^{-l}+r_i). \tag{4}$$

This likelihood function is the same as the one in the transmission CT context[14, 15] except that the projection data are less. The aim of ML-TS is to find an x which maximizes $L(x)$ by solving an optimization problem. The optimization of transmission problems is more difficult compared with the emission problems. A paraboloidal surrogate algorithm (PS) proposed by Erdogan is adopted in ML-TS algorithm[14]. The PS method takes root to the framework of optimization transfer[16]. The basic idea is that in each iteration a surrogate function (usually a convex function) $\varPhi(x)$ is constructed which has local properties of the likelihood function:

$$\begin{aligned}&\varPhi(x^n|x^n)=L(x^n),\\&\varPhi(x|x^n)\leqslant L(x),\forall x,\\&\nabla_x\varPhi(x|x^n)|_{x=x^n}=\nabla L(x)|_{x=x^n}\ ,\end{aligned} \tag{5}$$

x^n is the solution in the nth iteration. If the three conditions are fulfilled, maximizing $\varPhi(x)$ equals maximizing $L(x)$ and usually solving the optimization of $\varPhi(x)$ is easier. Due to the convexity of $L(x)$, Erdogan introduces the paraboloidal function that can be maximized easily to build the surrogate function. The paraboloidal surrogate function is:

$$\varPhi(x)=\sum_i q_i([Ax]_i) \tag{6}$$

where

$$q_i(l;l_i^k)=h_i(l_i^k)+\dot{h}_i(l_i^k)(l-l_i^k)+\frac{1}{2}c_i(l_i^k)(l-l_i^k)^2\ . \tag{7}$$

c_i is the coefficient of the paraboloidal function which compromises the convergence speed and the monotonicity condition[14]. Another algorithm with complex theoretical analysis is given by Ahn[15]. An accelerated ordered subsets (OS) version of Erdogan's algorithm is also practicable. The solution of ML-TS is achieved by maximizing $\varPhi(x)$ by iteration.

3 Results

The DEI-tomosynthesis experiments were performed at the 4W1A Station at BSRF. The setup was located approximately 43 m away from the source. The energy of the monochromatic X-rays was 10 keV. A black ant was scanned. The sample was rotated in 5.0° interval within 60°, and 12 projections were used in the tomosynthesis reconstruction. The pixel size is 10.9 μm. The size of the tomosynthesis reconstruction image is 800 pixels ×320 pixels.

The tomosynthesis reconstructions are shown in Fig. 2. Since tomosynthesis is a limited-angle problem, it is impossible to perform an exact reconstruction. Thus evaluating image quality of tomosynthesis

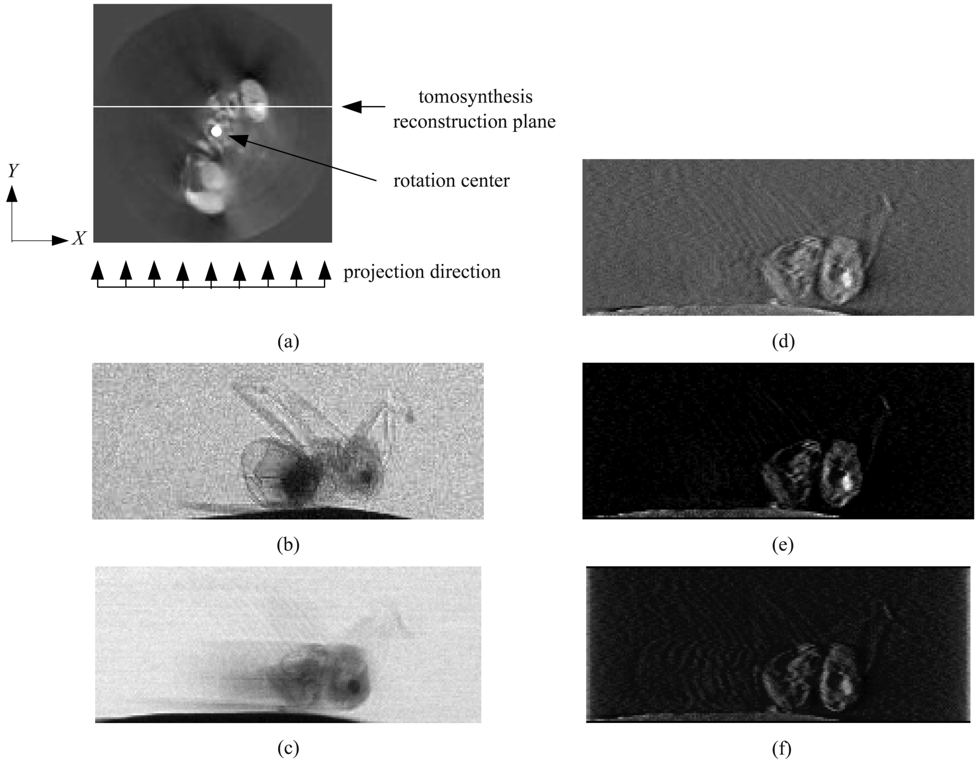

Fig. 2. Results of tomosynthesis reconstruction of the DEI data. The reconstructed parts are the head and the upper body of a black ant. (a) A 2D CT reconstruction image to indicate the projection direction, the rotation center and the tomosynthesis reconstruction plane; (b) The projection image; (c) BP algorithm, absorption data; (d) FBP algorithm, absorption data; (e) ML algorithm, absorption data, 6 iterations; (f) ML algorithm, the image data that are taken at a low-angle position of RC, 6 iterations.

is difficult[17]. In this preliminary study, a simple visual contrast is used as a figure of merit.

The reconstruction images are stretched to a grey range of [min, max] where min and max present the minimal and maximal pixel values of the image, respectively. The result of BP algorithm has the opposite contrast compared with the FBP and ML-TS algorithms because the reconstruction is just the addition of projection data of absorption while the results of FBP and ML-TS present attenuation coefficients. From Fig. 2, it can be seen that the result of ML-TS has a higher visual contrast than BP and FBP algorithms. In Fig. 3(e), the ML-TS result of the image data that are taken at a low-angle position of RC is also acceptable though the visual quality of the reconstruction is not as good as the result of absorption data. The artifacts are apparent compared with the apparent absorption data. The reason may be that the low-angle position image data contain refraction information, thus they don't follow a strict Poisson distribution.

4 Conclusions

In this paper, a maximum likelihood tomosynthesis algorithm is proposed to reconstruct 3D images of DEI data. We analyze the statistical model of DEI data, especially the apparent absorption data. The results of ML-TS have better contrast compared with conventional BP and FBP tomosynthesis algorithms in visual effects. The potential applications of ML-TS include biological and medical imaging, where lower radiation dose and shorter inspection time are expected. Further work includes establishing an accurate statistical model for the refraction-angle data or the scattering data and algorithm acceleration.

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References

1 Dobbins III J T, Godfery D J. Phys. Med. Biol., 2003, **48**: 65—106

2 Ziedses des Plantes. Acta Radiol., 1932, **13**: 182—192

3 Grant D G. IEEE Trans. Biomed. Eng., 1972, **19**: 20–8

4 WU T, Moore R H, Rafferty E A et al. Medical Physics, 2004, **31**: 2636—2647

5 Suryanarayanan S, Karellas A, Vedantham S et al. Academic Radiology, 2000, **7**: 1085—1097

6 Chapman D, Thomlinson W, Arfelli F et al. Rev. Sci. Instrum., 1996, **67:** 3360

7 Maksimenko A, Yuasa T, Ando M et al. Appl. Phys. Lett., 2007, **91**: 234108-3

8 Chapman D, Nesch I, Hasnah M O et al. Nucl. Instrum. Methods Phys. Res., Sect. A, 2006, **562**: 461—467

9 Vine D J, Paganin D M. Appl. Phys. Lett., 2007, **91**: 254110-3

10 CHEN Z Q, DING F, HUANG Z F et al. Chin. Phys. C (HEP & NP), 2009, **33**(11): 961—966

11 Natterer F, Wübbeling F. Mathematical Methods in Image Reconstruction. Philadelphia: SIAM, 2001. 10—13

12 Lange K, Carson R. J Comput Assist Tomogr., 1984, **8**: 306—316

13 Schultz L J. Cosmic Ray Muon Radiography. Doctor dissertation, Portland State University, 2003. 53—57

14 Erdogan H, Fessler J. In Proc. IEEE Intl. Conf. On Image Processing, 1998, **2**: 680—684

15 Ahn S, Fessler J A, Blatt D et al. Proc. IEEE Nuc. Sci. Symp. Med. Im. Conf., 2004, **5**: 2835—2839

16 Lange K, Hunter D R, YANG I. Journal of Computational and Graphical Statistics, 2000, **9**: 1—20

17 Suryanarayanan S, Karellas A, Vedantham S et al. Radiology, 2002, **225**: 801—807