Cone-Beam X-ray Luminescence Computed Tomography Reconstruction Based on Huber Markov Random Field Regularization

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ABSTRACT

In recent years, cone-beam X-ray luminescence computed tomography (CB-XLCT) has drawn much attention with the development of X-ray excited nanophosphors. Compared with traditional bio-optical imaging modalities such as bioluminescence tomography (BLT) and fluorescence molecular tomography (FMT), CB-XLCT can effectively improve imaging sensitivity and depth because of the reduction of background fluorescence and the high penetrability of X-rays. However, due to high degree of scattering of light through biological tissues, the reconstruction of CB-XLCT is inherently ill-conditioned. To solve the ill-posed inverse problem, appropriate priors or regularizations are needed to facilitate the reconstruction. Based on the fact that adjacent pixels generally have the same or similar concentration and in order to further balance the degree of regional smoothness and edge sharpening, a prior information model based on Huber Markov Random Field (HuMRF) was established to constrain the reconstruction process of CB-XLCT. Mice experiments indicate that compared with the traditional ART and ADAPTIK method, the proposed method could improve the image quality of CB-XLCT significantly in terms of target shape, localization accuracy and image contrast.

Keywords: X-ray luminescence computed tomography, image reconstruction techniques, Huber Markov Random Field, mice experiments

1. INTRODUCTION

With the advances of X-ray excitable nanophosphors, cone-beam X-ray luminescence computed tomography (CB-XLCT) has attracted more attention for its promising performance[1]. In CB-XLCT, X-ray excitable nanophosphors are used as imaging probes and emit visible or near-infrared (NIR) light when irradiated by X-rays. The photons excited by X-rays arrive at the surface of the imaging object and can be measured by sensitive photon detectors. By solving an inverse problem using an appropriate imaging model of X-ray and photon transport, the three-dimensional (3-D) distribution of the nanophosphors in the imaged object can be resolved. Compared with traditional bio-optical imaging modalities such as bioluminescence tomography (BLT) and fluorescence molecular tomography (FMT), CB-XLCT can effectively improve imaging sensitivity and depth because of the reduction of background fluorescence and the high penetrability of X-rays[2]. However, due to high degree of scattering of light through biological tissues, the reconstruction of CB-XLCT is inherently ill-conditioned. In order to improve the reconstruction quality of CB-XLCT, the priori information is needed to constrain the reconstruction process.

In this study, we propose a reconstruction approach based on Huber Markov Random Field (HuMRF) for the CB-XLCT reconstruction. The remainder of this paper is organized as follows. In Section 2, the proposed method is described in detail. In Section 3, the mice experiments design and results are described for the performance evaluation of the proposed reconstruction approach. Finally, conclusion is given in Section 4.

2. METHODS

2.1 Forward model of XLCT and Inverse Problem based on the proposed GHuMRF algorithm

Based on the forward model of CB-XLCT[3]:

$$Wn = \Phi_{meas} \tag{1}$$

In practical application of XLCT, noise of the XLCT imaging system needs to be considered, and equation (1)

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becomes:

$$y = \Phi_{meas} + \varsigma = Wx + \varsigma \tag{2}$$

where $y = [y_1, y_2, \cdots, y_M]^T$ represents the actual fluorescence signals measured on the surface of the imaging object, $\varsigma = [\varsigma_1, \varsigma_2, \cdots, \varsigma_M]^T$ is the noise of the system,W is the weight matrix, $x = n$ represents the unknown distribution of nanophosphors in the imaging object.

Based on Bayes theory, the maximum a posteriori (MAP) estimation of the unknown distribution of nanophosphors in the imaging object can be expressed as[4]:

$$\hat{x}_{MAP} = \arg\max_x \{\log p(x/y)\} = \arg\max_x \{\log p(y/x) + \log p(x)\} \tag{3}$$

where $p(x/y)$ represents the posterior probability density function, $p(y/x)$ represents the conditional probability function (measurement model), $p(x)$ represents the priori probability density function (priori model).

Since the working temperature of the EMCCD camera is very low, the measurement model is constructed based on a shot-noise model, which assumes the independent measurement noise can be described by a Gaussian distribution:

$$p(y/x) = \frac{1}{(\pi\kappa)^M |\Lambda_y|} \exp\left[-\frac{1}{\kappa} \|y - Wx\|^2_{\Lambda_y^{-1}} \right] \tag{4}$$

where M represents the number of measurement points，κ is the unknown hyperparameters related to noise variance，Λ_y is the covariance matrix of the fluorescence measurement signal.

Based on the adjacent pixels generally have the same or similar concentration and in order to further balance the degree of regional smoothness and edge sharpening, the priori model is constructed based on Huber Markov Random Field (HuMRF):

$$p(x) = \frac{1}{Z\sigma^N} \exp\left[-\frac{1}{2\sigma^2} \sum_{j=1}^{N} \sum_{k \in \partial j} b_{j-k} \phi(\Delta) \right] \tag{5}$$

where $\Delta = x_j - x_k$, $\phi(\Delta) = \begin{cases} \Delta^2 & |\Delta| \le \delta \\ 2\delta|\Delta| - \delta^2 & |\Delta| > \delta \end{cases}$, δ is an adjustable parameter to balance the smoothness of the region and the sharpness of the boundary, b_{j-k} is the weight coefficients between the jth and kth pixels which is inversely proportional to the distance between the pixels.

2.2 Quantitative evaluation

The quality of reconstructed CB-XLCT images was evaluated quantitatively by several indexes including the location error (*LE*), dice similarity coefficient (*DICE*) and contrast-to-noise ratio (*CNR*)[3].

LE evaluates the localization accuracy of the reconstructed target, which is defined as the Euclidean distance error between the centers of true and reconstructed targets:

$$LE = \|\mathbf{L_r} - \mathbf{L_t}\|_2 \tag{6}$$

where $\boldsymbol{L_r}$ and $\boldsymbol{L_t}$ denote the centers of the reconstructed and true targets, respectively.

DICE reflects the similarity of the true and reconstructed targets and can be calculated by:

$$DICE = \frac{2|\mathbf{ROI_r} \cap \mathbf{ROI}_t|}{|\mathbf{ROI_r}| + |\mathbf{ROI_t}|} \tag{7}$$

where $\boldsymbol{ROI_t}$ and $\boldsymbol{ROI_r}$ denote the regions of true and reconstructed targets, respectively, and $|\cdot|$ defines the number of voxels in a region.

CNR is used for quantitative evaluation of noise and artifacts in reconstructed images, as shown below:

$$CNR = \frac{|\mu_{ROI} - \mu_{BCK}|}{(w_{ROI}\sigma_{ROI}^2 + w_{BCK}\sigma_{BCK}^2)^{1/2}} \tag{8}$$

where *ROI* and *BCK* denote the target and background regions of the imaged object, w_{ROI} and w_{BCK} are weighting factors determined by the relative volumes of the target and background, μ_{ROI} and μ_{BCK} are the mean intensity values of the *ROI* and *BCK*, and σ_{ROI}^2 and σ_{BCK}^2 represent the variances of the ROI and BCK, respectively.

3. EXPERIMENTAL DESIGN AND RESULTS

Mice experiments were performed to evaluate the performance of the proposed method based on the custom-developed CB-XLCT system in our laboratory. All experiments were conducted in compliance with the provisions of the Animal Ethics Review Committee of the Air Force Military Medical University. For comparison, two traditional methods, algebra reconstruction technique (ART), and adaptive tikhonov regularization (ADAPTIK) were also implemented to reconstructed the image.

A female BALB/c nude mice was used in this experiment. A small glass tubes (3mm in diameter) filled with Y_2O_3: Eu^{3+} (60mg/ml) was embedded into the abdominal cavity of mice to serve as the nano-probe in XLCT imaging. During imaging experiments, the mice were fixed on the rotation stage. The voltage and current of the X-ray source were set as 50kVp and 1mA, respectively. The mice was rotated from 0° to 360° and the optical images were obtained every 15° by the EMCCD camera. The exposure time of the EMCCD camera was set as 2s, with the EM gain set as 260.

The XLCT tomographic images were reconstructed with different algorithms in the mouse experiments, as shown in Fig. 1. All the reconstruction results are normalized based on their maximum values. Fig. 1.（c），（e），（g）show the reconstruction results based on ART, ADAPTIK and the proposed methods respectively. Fig. 1. (d), (f), (h) are the fusion results of XLCT and XCT reconstructed images. It can be seen that compared with the traditional ART and ADAPTIK method, the proposed method could improve the image quality of CB-XLCT significantly in terms of target shape, localization accuracy and image contrast.

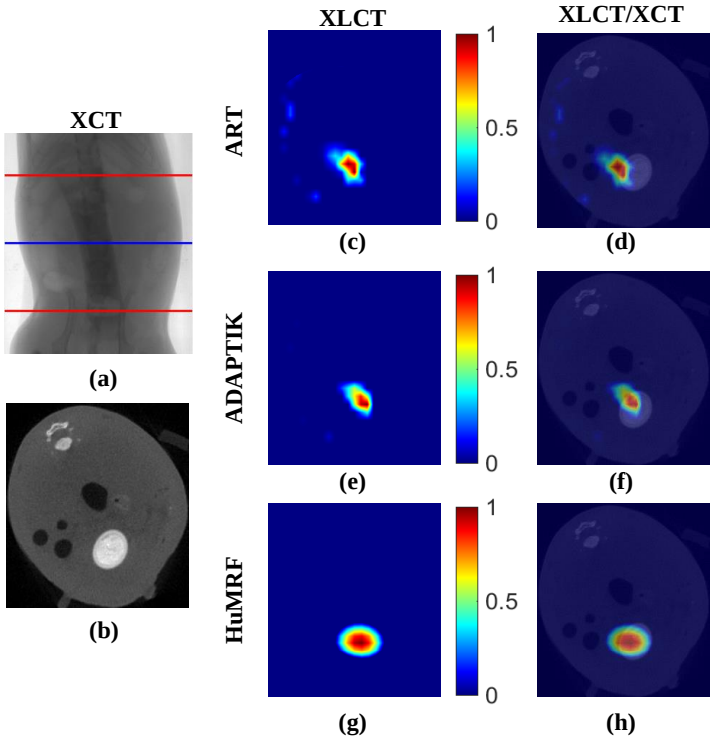

Figure 1. The tomographic images were reconstructed based on ART, ADAPTIK and the proposed methods.

The quality of reconstructed CB-XLCT images is given in Table 1. For the Mice experiments, the reconstruction results based on the proposed the proposed GHuMRF algorithm yield the highest Dice and CNR with lowest LE. The results indicate that proposed GHuMRF algorithm performs better in target location, shape recovery and image contrast, when compared to the conventional reconstruction methods of ART and ADAPTIK, which further confirm the observation in Fig. 1.

Table 1 Quantitative Evaluation on Mice experiments reconstructions using different methods

	LE(mm)	**DICE**	**CNR**
ART	2.5	0.51	2.63
ADAPTIK	1.8	0.6	3.5
GHuMRF	0.9	0.9	5.28

4. DISCUSSION AND CONCLUSIONS

In this study, a reconstruction approach based on HuMRF regularization is proposed for the CB-XLCT inverse problem. Mice experiments indicate that compared with the traditional ART and ADAPTIK method, the proposed method could improve the image quality of CB-XLCT significantly in terms of target shape, localization accuracy and image contrast.

It should be noted that Both Gaussian noise model[5] and Poisson noise model[6] can be used to simulate the measurement noise of EMCCD camera. Generally, Poisson distribution tends to Gaussian distribution with the increase of sample size. In this paper, the Gaussian noise model is used to simulate the measurement noise of EMCCD camera. In the further in vivo imaging research, the Poisson noise model can be used to construct the measurement model, because the number of photons collected by EMCCD camera is relatively lower.

In the mouse experiment, the mice were placed in deep anesthesia. When the turntable rotates, it uses a low speed of 6°/s while maintaining a uniform rotation speed, to minimize the adverse effects of internal organ movement in mice during data collection. Moreover, the mouse was monitored throughout the data acquisition process to ensure that its position would not change. Therefore, in this paper, for mouse experiments, motion correction was not performed during reconstruction.

It is necessary to accurately segment the organs of the imaging object, because of giving corresponding optical parameters to different organs is important to obtain high-quality reconstructed images. Therefore, a more accurate image segmentation algorithm needs to be used for organ segmentation in mice

In this paper, because CT reconstruction requires more projections, XCT projection data and optical detection signals are collected twice. In future experiments, the simultaneous acquisition of XCT projection data and optical detection signals can reduce the scanning time, radiation dose and the impact of organ movement between two scans on the reconstruction results.

In summary, based on Bayes theory, a CB-XLCT reconstruction method based on GHuMRF algorithm is proposed in this paper. Compared with the traditional ART and ADAPTIK method, the GHuMRF algorithm add spatial constraints between adjacent pixels during reconstruction, which improves the image quality of CB-XLCT reconstruction. In the further study, more prior information constraints can be added to CB-XLCT reconstruction based on Bayes theory to improve the image quality of CB-XLCT.

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Disclosures

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REFERENCES

[1] G. Pratx, C. Carpenter, C. Sun, and L. Xing, "X-ray luminescence computed tomography via selective excitation: a feasibility study," IEEE Trans Med Imaging, 29(12), 1992-1999 (2010).

[2] T. Liu, J. Rong, P. Gao, H. Pu, W. Zhang, X. Zhang, et al., "Regularized reconstruction based on joint L 1 and total variation for sparse-view cone-beam X-ray luminescence computed tomography," Biomed Opt Express, 10(1), 1-17 (2019).

[3] T. Liu, J. Rong, P. Gao, W. Zhang, W. Liu, Y. Zhang, et al., "Cone-beam x-ray luminescence computed tomography based on x-ray absorption dosage," J Biomed Opt, 23(2), 026006.1-026006.11 (2018).

[4] G. Zhang, F. Liu, J. Liu, J. Luo, Y. Xie, J. Bai, et al., "Cone beam x-ray luminescence computed tomography based on Bayesian method," IEEE Trans Med Imaging, 36 (1), 225-235 (2017).

[5] D. Chen, S. Zhu, H. Yi, X. Zhang, D. Chen, J. Liang, et al., "Cone beam x-ray luminescence computed tomography: a feasibility study," Med Phys, 40 (3), 031111 (2013)

[6] W. Cong, H. Shen, and G. Wang, "Spectrally resolving and scattering-compensated x-ray luminescence/fluorescence computed tomography," J Biomed Opt, 16(6), 066014.1-066014.7 (2011).