



Multi-mounted X-ray cone-beam computed tomography

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ABSTRACT

As a powerful nondestructive inspection technique, X-ray computed tomography (X-CT) has been widely applied to clinical diagnosis, industrial production and cutting-edge research. Imaging efficiency is currently one of the major obstacles for the applications of X-CT. In this paper, a multi-mounted three dimensional cone-beam X-CT (MM-CBCT) method is reported. It consists of a novel multi-mounted cone-beam scanning geometry and the corresponding three dimensional statistical iterative reconstruction algorithm. The scanning geometry is the most iconic design and significantly different from the current CBCT systems. Permitting the cone-beam scanning of multiple objects simultaneously, the proposed approach has the potential to achieve an imaging efficiency orders of magnitude greater than the conventional methods. Although multiple objects can be also bundled together and scanned simultaneously by the conventional CBCT methods, it will lead to the increased penetration thickness and signal crosstalk. In contrast, MM-CBCT avoids substantially these problems. This work comprises a numerical study of the method and its experimental verification using a dataset measured with a developed MM-CBCT prototype system. This technique will provide a possible solution for the CT inspection in a large scale.

1. Introduction

X-RAY computed tomography (X-CT) provides nondestructively the three dimensional distribution of attenuation coefficients of samples from their projection images recorded by detectors [1–3]. As a powerful imaging inspection technique, it has been used more and more extensively in the fields of medicine, industry and homeland security since its invention by Godfrey Newbold Hounsfield in 1970s [4–12]. The imaging speed, determined by the scanning and the image reconstruction, is one of the major obstacles to the applications of X-CT. Currently the reconstruction speed has already been improved drastically by using the graphic processing units (GPU) and the compute unified device architecture (CUDA) from the company nVIDIA [13]. We need to reduce the time on scanning in order to further improve the imaging efficiency.

Reviewing the development of X-CT shows the efforts to promote the imaging speed [14–16]. The earliest 1st generation CT scanner works in single pencil-beam translate/rotate mode and as slow as a snail to execute a complete CT scanning. The following 2nd adopts a narrow-angle fan-beam translate/rotate mode and the scanning time decreases significantly. The 3rd is based on fan-beam rotate-only mode and improves drastically the imaging efficiency due to the removal of translate movement. The 4th adopts stationary detector-ring to reduce the scanning time. The 5th is called electron-beam CT and used to

image beating hearts. Since then, many novel CT techniques have been proposed to improve the imaging speed, such as multi-slice CT (MSCT) [17,18], dual source CT [19], inverse geometry CT [20] and single circular orbit cone-beam CT (CBCT) [21–25]. Although these techniques have improved tremendously the scanning efficiency, they work in single-mounted mode and need to scan the objects one by one. It may be reasonable for clinic diagnosis since the inspection task is specific for each patient. However, it is difficult to keep pace with the industrial mass production and not acceptable for the inspection in a large scale [26]. Until now the conventional single-mounted CT (SMCT) is still applied to industry as a casual inspection technique not as a general tool [26]. Recently, we reported a fan-beam two-dimensional multi-mounted CT (MMCT) method and its first engineering implementation [26]. Permitting the rotation scanning of multiple objects simultaneously without the increased penetration thickness and signal crosstalk, it has the potential to improve the imaging efficiency and suppress the artifacts from the beam hardening and the scatter.

The new aspect of the work presented here is to extend MMCT methods from fan-beam two-dimension to cone-beam three dimension. The formed multi-mounted cone-beam CT (MM-CBCT) approach enables the cone-beam scanning of multiple objects simultaneously. The three dimensional CT slice images of the inspected objects are then

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reconstructed by the corresponding statistical iterative reconstruction algorithm. It can achieve an imaging efficiency orders of magnitude greater than the conventional CBCT methods.

In the following sections, the multi-mounted cone-beam scanning geometry and the corresponding statistical iterative reconstruction algorithm are first described. Next by computer simulation, the validity of the proposed MM-CBCT method is investigated. Finally the developed experimental system is described and the experimental results are presented.

2. Methods and materials

2.1. Scanning geometry

Fig. 1(a) and (b) depict the scanning geometry of the conventional single-mounted CBCT, in which a sample holder rotates the object over 360° during data acquisition. At each view angle, the cone-beam X-ray emitted from the source hits the inspected objects and the opposite flat panel detector records the two dimensional projection image. The 3D volumes of the objects can finally be reconstructed by CT reconstruction algorithms. Because only one rotation axis exists in the conventional single-mounted CBCT, it needs to scan objects one by one and is time-consuming. Sometimes the conventional single-mounted CBCT can also implement the cone-beam scanning of multiple objects bundled together depicted in Fig. 1(c) and (d). However, Fig. 1(b) and (d) show obviously that the penetration thickness, indicated by l , will increase and the signal crosstalk among these objects will happen. The caused artifacts will degrade severely the slice images.

Fig. 1(e) and (f) illustrate the scanning geometry of the proposed MM-CBCT. It is similar to the conventional single-mounted CBCT. The significant modification is the replacement of the holder by a multi-mounted rotation table. It drives multiple rotation axes along the direction parallel to the detector and permits the cone-beam rotation scanning of multiple objects simultaneously supported by the multi-axes numerical control synchronization technique. In our current work, the scanning geometry of the proposed MM-CBCT has four rotation axes. Obviously with one rotation of the multi-mounted table, it can provide the dataset equivalent to that of a conventional single-mounted CBCT scanner with multiple rotations. Consequently, it has the potential to promote the imaging efficiency without the increase of the penetration thickness and the signal crosstalk.

2.2. Reconstruction algorithm

CT image reconstruction from the recorded projections belongs to inverse problem in mathematics. Many advanced algorithms have been developed for CT image reconstruction since Radon's great contribution in 1917. Most of them are classified into two categories: analytical and iterative methods [21,22,27–29]. The FDK algorithm proposed by Feldkamp, Davis and Kress is the representative of the analytical approaches and also the most popular one because of the good balance between reconstruction quality and speed [21]. Generally it can perform accurate reconstruction when the projection dataset is complete and there is no mechanical error. Statistical iterative reconstruction (SIR) is a typical iterative method [27,28]. It is based on the physical and geometrical models of the imaging system and can achieve a high-quality reconstruction by regularization operation when applied to low-dose, noisy and incomplete dataset. It works well on suppressing noise and improving spatial resolution. It also performs better than FDK when applied to large cone-angle dataset.

In the proposed cone-beam MM-CBCT geometry depicted in Fig. 1(e) and (f), there exists an angle a between the central X-ray beam, which is perpendicular to the detector plane and indicated by the dashed line d , and the X-ray beam connecting the X-ray source focus and the rotation center. The analytical methods require that these two beams

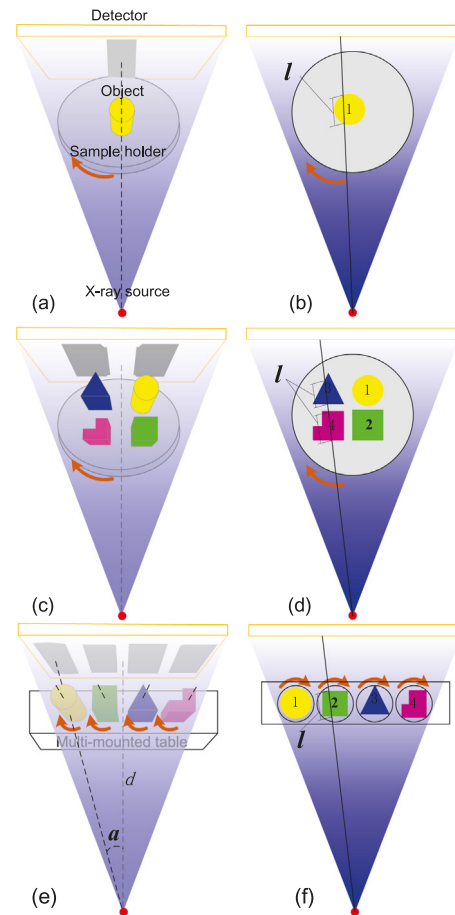


Fig. 1. The three-dimensional cone-beam CT schematics. (a) and (b) are for the conventional single-mounted CBCT with one object. (c) and (d) are for the conventional single-mounted CBCT with multiple objects. (e) and (f) are for the proposed multi-mounted CBCT. (b), (d) and (f) correspond to the fan-beam schematics of the central horizontal cross-section. l represents the penetration thickness. a represents the angle between the central X-ray beam which is perpendicular to the detector plane and indicated by the dashed line d and the X-ray beam connecting the X-ray source focus and the rotation center.

are coincide with each other. Clearly, the proposed cone-beam MM-CBCT geometry cannot meet this condition. Moreover, large cone-angle geometrical layout is generally used within this system to improve the imaging field of view. Considering these two factors, the penalized likelihood (PL) SIR algorithm is adopted to reconstruct the 3D volume images for the proposed MM-CBCT.

The PL method substantially solves the optimization problem expressed in Eq. (1) and gets iteratively the reconstructed image $\bar{\mu}$ from the recorded projection dataset I to maximize the likelihood function $L(\mu, I)$ of the objective image μ and penalize the image roughness $R(\mu)$ with the strength γ . Eq. (2) shows one of the solutions of Eq. (1) proposed by P J Green [27] and was used in our work.

$$\bar{\mu} = \operatorname{argmax}_{\mu} L(\mu, I) - \gamma R(\mu) \quad (1)$$

$$\mu_j^{n+1} = \frac{\mu_j^n}{\sum_{i=1}^N c_{ij} + \gamma \left(\frac{\partial R(\mu_j^n)}{\partial \mu_j} \right)} \sum_{i=1}^N c_{ij} \frac{I_i}{\sum_{j=1}^M c_{ij} \mu_j^n} \quad (2)$$

In Eq. (2), μ_j^{n+1} represents the value of the j th voxel of the reconstructed image μ at the $(n + 1)$ th iteration. The number of the projections is N and the number of the voxels M . c_{ij} is a geometrical weighting factor and describes the contribution of the j th voxel to the i th

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