

A new algorithm for motion adapted cone beam CT reconstruction using an advanced motion model

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Abstract

Purpose: To describe a novel algorithm for motion adapted cone beam CT (CBCT) reconstruction useful for 4D radiation therapy of lung tumors.

Methods: The presence of internal motion during CBCT acquisition is a challenge to CBCT reconstruction. We report on a novel algorithm that adapts to the presence of lung motion by using a free-breathing acquisition of CBCT ray sums, a surrogate breathing signal, and an advanced motion model [1]. The new algorithm solves the reconstruction problem as a feasibility problem with an iterative projection method. We are testing and optimizing the algorithm with a modification of the 4D FORBILD thorax phantom [2] and the simulation package jSNARK [3].

Results: We simulated 25 helical scans of the 4D phantom and a motion described by 5 cosine terms. For helical-CT reconstruction, we used the Katsevich algorithm [4]. The deformable image registration toolbox Elastix was used to register the image from the first helical scan to the remaining 24 images establishing the motion model parameters¹. We are currently simulating a CBCT acquisition of the 4D phantom and will use it to reconstruct the reference breathing image of the phantom with the new algorithm.

Conclusions: A novel CBCT motion-adapted reconstruction algorithm in combination with advanced breathing motion model has been developed for applications in particle therapy.

Introduction

Cone beam CT (CBCT) is now frequently used for 3D image guidance in radiation therapy including proton & ion therapy. In the case of lung tumors, CBCT has a problem with motion blurring artifacts when the patient is free-breathing, making this technique less useful for pretreatment image guidance. While motion could be restricted (for example, with deep inspiration breath hold), this is rarely feasible in lung tumor patients with reduced respiratory capacity.

We (the authors) arrived at this juncture looking for a reconstruction solution for free-breathing patients undergoing proton CT. Proton CT reconstruction, as previously developed by us, registers individual protons passing through a patient at a given instant in time when the lung is in a certain motion state. However, without knowledge of tissue motion, it is impossible to reconstruct a blurring-free image from proton CT data. The same is true if we use individual projection rays from an x-ray CBCT in combination with an iterative reconstruction algorithm such as ART. We have set out to solve this problem.

Solution strategy part 1: Find an adequate motion model

D. Low and colleagues at UCLA previously showed that the deformation (including motion and rotation and change of shape) of a lung tissue voxel relative to an arbitrary reference phase during quiet, free respiration can be described by a linear approximation of tidal volume (v) and airflow (f) as surrogate breathing state variables described by

$$\vec{X}(v, f; \vec{X}_0) = \vec{X}_0 + \vec{\alpha}(\vec{X}_0)v + \vec{\beta}(\vec{X}_0)f$$

where $\vec{\alpha}(\vec{X}_0)$ and $\vec{\beta}(\vec{X}_0)$ relate the deformation of the tissue location $\vec{X}(v, f; \vec{X}_0)$ relative to the tissue at reference location \vec{X}_0 to the tidal volume and airflow including motion hysteresis.

Solution strategy part 2: Find a suitable reconstruction technique

If we know how tissue voxels are deformed at any given motion phase, for a given v and f , we can, in principle, relate the tissues contained in the object voxel grid at the time when these parameters were measured to those at a reference phase which we aim to reconstruct using the motion model shown above. This leads to a new set of equations which one can solve with ART. Since the reconstruction takes now motion into account, we call this algorithm **motion-adapted algebraic reconstruction technique or MAART**.

Methods and First Results

We have implemented a successive series of moving geometric objects with increasing complexity to test the MAART algorithm. The first series consisted of a simple elliptical 2D object that was translated, rotated, and deformed to 5 discrete motion states. A simulated fan-beam x-ray CT acquisition with 360 projections of the moving object was obtained with one of the 5 motion states assigned cyclically to each projection. The CT data were reconstructed with ART and MAART (Fig.1) where the MAART algorithm utilized Elastix. In the next phase, we created a 3D version (ellipsoid) of the moving and deforming object and performed a 3D CBCT, again reconstructed with ART and MAART (Fig. 2). Lastly we attempted to apply ART and MAART to the synthetic FORBILD phantom with a moving ellipsoidal tumor embedded in the right lung and motion surrogate signals simulated (Fig. 3).

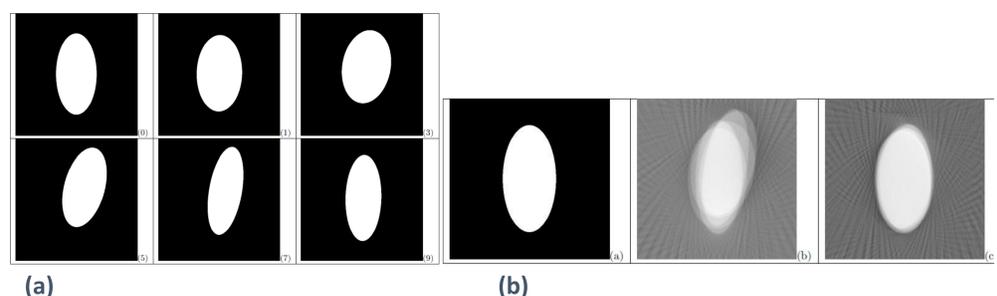


Figure 1. (a) Original 2D motion phantom. with reference state upper left. (b) Reference state of the 2D motion phantom (left) reconstructed with ART (center) and MAART (right). Note the reduction of blurring with MAART

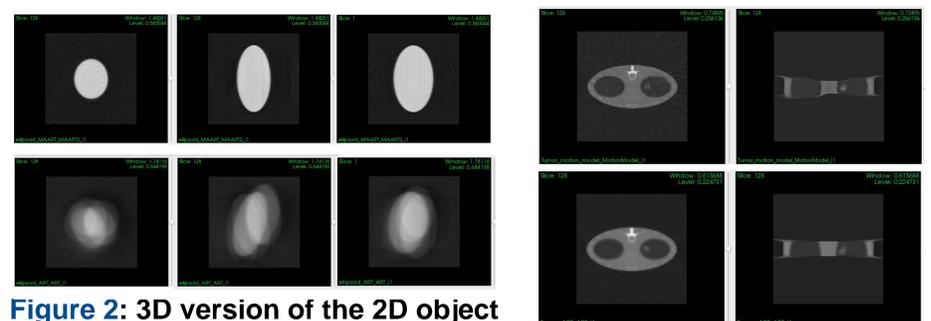


Figure 2: 3D version of the 2D object from above: (Top) Axial, coronal, and sagittal reconstructions with MART of one motion state. (Bottom) Same images reconstructed with ART.

Figure 3: FORBILD moving phantom reconstruction: (Top) Axial and coronal MAART reconstructions (Bottom) Axial and coronal ART reconstructions.

References

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