Registration Based SIRT: A reconstruction algorithm for 4D CT

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Abstract

The goal of 4D computed tomography (4D CT) is to study the temporal behavior of a 3D sample with a sufficiently high temporal and spatial resolution. Conventionally, the sample is sequentially scanned, resulting in datasets of successive time frames. Each of these datasets is then independently reconstructed. This framework results in a trade-off between the temporal resolution and the signal to noise ratio (SNR) of the reconstructed images. The proposed registration based simultaneous iterative reconstruction technique (RB SIRT) allows shortening the acquisition time per time frame, thereby improving the temporal resolution, without decreasing the SNR. To this end, the algorithm estimates the deformation field between different time frames, which allows adding projections of other time frames into the reconstruction of a particular time frame. The technique was validated on a real dynamic experiment of a polyurethane foam sample. The reconstructions obtained with RB SIRT have a significantly higher SNR with respect to conventional reconstructions.

Keywords: 4D CT, dynamic, reconstruction algorithm, computed tomography, image registration

1 Introduction

4D (3 spatial dimensions + time) computed tomography (CT) is able to study dynamic processes in a non-destructive manner. This data is often indispensable for validating models of dynamic processes. Conventionally, several CT datasets (= time frames) are acquired sequentially which are independently reconstructed. However, if the object is not nearly stationary during the acquisition of a single time frame, blurry artifacts degrade the reconstructed images. A straight forward method to avoid these artefacts and improve the temporal resolution is to shorten acquisition time of a single dataset by shortening integration time or lowering the number of projections. This results, however, in a decreased signal to noise ratio (SNR) of the reconstructed images. The decrease of SNR can be avoided by exploiting data redundancy present in 4D CT datasets. The proposed reconstruction method achieves this by estimating the deformation of the object. This allows including projections of other time frames into the reconstruction of a particular time frame without introducing motion artifacts.

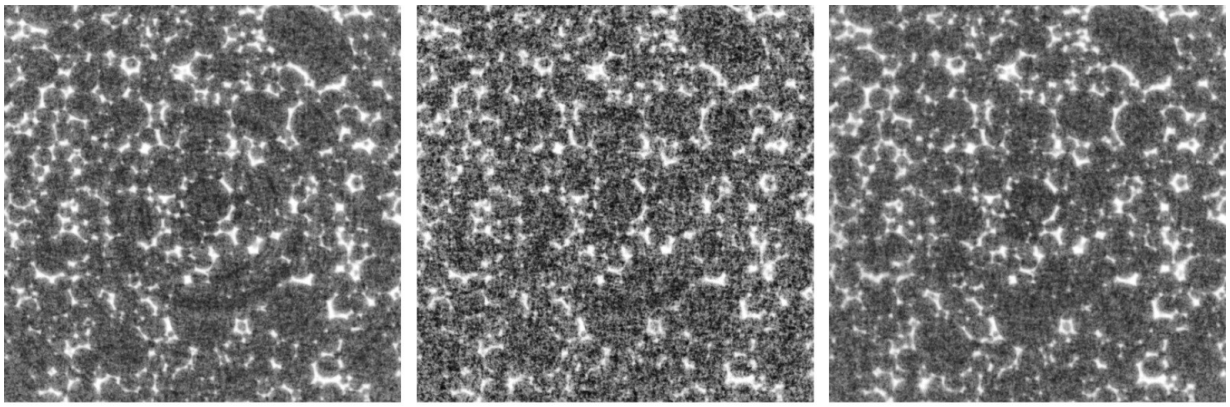
2 Methods

The reconstructed object at time frame i can be represented as a column vector $\boldsymbol{x}_{(i)} = (x_{(i),k}) \in \mathbb{R}^N$. The vector $\boldsymbol{p}_{(i)} = (p_{(i),k}) \in \mathbb{R}^{M_{(i)}}$ denotes all the acquired projections of the object at time frame i. The projections are simulated with the forward model: $\boldsymbol{p}_{(i)} = A_{(i)}\, \boldsymbol{x}_{(i)}$, where $A_{(i)} = (a_{(i),kl}) \in \mathbb{R}^{M_{(i)} \times N}$. To reconstruct the object at time frame i we propose the following SIRT [1] based iterative reconstruction algorithm:

$$\boldsymbol{x}_{(i)}^{(k+1)} = \boldsymbol{x}_{(i)}^{(k)} + \sum_j w_{ij} \tau_{(i\to j)}^{-1}\, C_{(j)} A_{(j)}^T R_{(j)} \left(\boldsymbol{p}_{(j)} - A_{(j)} \tau_{(i\to j)} \boldsymbol{x}_{(i)}^{(k)} \right) \tag{1}$$

Where $C_{(j)} = (c_{(j),kl}) \in \mathbb{R}^{N \times N}$ is a diagonal matrix with $c_{(j),ll} = 1 / \sum_k a_{(j),kl}$ and $R_{(j)} = (r_{(j),kl}) \in \mathbb{R}^{M_{(i)} \times M_{(i)}}$ is a diagonal matrix with $r_{(j),kk} = 1 / \sum_l a_{(j),kl}$. The operator $\tau_{(i\to j)}$ transforms the object at time frame i to its state at time frame j: $\boldsymbol{x}_{(j)} = \tau_{(i\to j)} \boldsymbol{x}_{(i)}$. The weights w_{ij} are normalized such that $\sum_j w_{ij} = 1$. For each time frame j, the proposed reconstruction algorithm transforms the current estimate of $\boldsymbol{x}_{(i)}$ to the j'th time frame and then calculates a SIRT update using the projection data of time frame j. This SIRT update is then transformed back to time frame i, weighted with w_j and added to the current total update of $\boldsymbol{x}_{(i)}^{(k)}$. This is repeated for all time frames after which the total update is added to $\boldsymbol{x}_{(i)}^{(k)}$. The deformation operators $\tau_{(i\to j)}$ and their inverse (see equation (1)) are unknown and have to be estimated. To this end, each time frame is first conventionally reconstructed using only the projections corresponding to that time frame. Afterwards, these conventional reconstructions are pairwise registered with each other resulting in deformation vector fields (DVFs). The registration, performed with the registration software Elastix [2], estimates the parameters of a B-spline deformation model. The inverse DVFs are calculated as described in Chen et al. [3]. The weights w_{ij} reflect the accuracy of the corresponding DVFs.

The proposed method was implemented in Matlab, the forward and backprojections were performed with the ASTRA toolbox [4]. We will refer to the reconstruction algorithm as registration based SIRT (RB SIRT).



(a) (b) (c)

Fig 1: Reconstructed image of the foam dataset (time frame 3): (a) SIRT reconstruction with 2000 projections/time frame, (b) SIRT reconstruction with 1000 projections/time frame, (C) RB SIRT reconstruction with 1000 projections/time frame.

3 Experiments and results

A dynamic x-ray CT dataset was acquired by Inside Matters with a gantry-based high-resolution scanner [5]. A polyurethane foam sample (provided by Huntsman) of 11mm high was loaded in a compression stage which was mounted in the scanner. Seven CT datasets were acquired. During these scans the sample was compressed $l \cdot 0.5\ mm$, where l=0,..,L-1 is the time frame number. Each dataset (= time frame) consists out of 2000 equiangular projections (1316 ×1312 pixels, pixel size 0.1 mm) acquired over an angular range of 360 degrees. All reconstructions were calculated on a 1316x1316x401 isotropic voxel grid with a voxel size of 16μm.

Each time frame was reconstructed with three different methods: Firstly, conventional SIRT with 2000 projections/time frame. Secondly, conventional SIRT with 1000 projections/time frame and, thirdly, RB SIRT with 1000 projections/time frame. RB SIRT estimates the deformation and includes the projections of a single neighboring time frame to the reconstruction of a particular time frame. Reconstructions with only 1000 projections were performed with projections with projection numbers $1 + (l \bmod 2), 3 + (l \bmod 2), \ldots, N$, where l is the time frame number and N the total number of acquired projections/time frame. As such neighboring time frames have interleaved projections.

The SIRT reconstruction with 2000 projections/time frame (Fig 1(a)) shows the foam structures very clearly. The SNR is sufficiently high to observe small foam structures. Furthermore, the reconstructed images are degraded with ring artefacts. The SIRT reconstruction with only 1000 projections/time frame (Fig 2(b)) has a visibly lower SNR than the SIRT reconstruction with 2000 projections/time frame. High frequency components of the images are heavily degraded with noise. Ring artefacts are almost invisible due to the low SNR. The RB SIRT reconstruction (1000 projections/time frame) possesses a similar SNR as the SIRT reconstruction with 2000 projections/time frame. Small details are clearly visible in the images and no ring artefacts are observed.

4 Conclusions

The performed experiment shows that the RB SIRT algorithm is able to successfully exploit the data redundancy present in 4D CT datasets. It allows lowering the acquisition time of a single time frame without compromising the SNR of the reconstructed images. This is achieved by estimating the deformation between different time frames which allows including projections of different time frames to the reconstruction of a certain time frame without introduction of motion artefacts. An additional advantage of the RB SIRT algorithm is its ability to remove ring artefacts.

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