Region-based SIRT algorithm for the reconstruction of phase bins in dynamic micro-CT

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Introduction
In dynamic micro-CT, the goal is to visualize the interior of a time-varying object at different points in time. If the scanned object is reconstructed without taking into account the object’s motion, the reconstructed image will be blurred.

A standard approach to compensate for this motion is to incorporate a motion model in the reconstruction algorithm. The motion model can be estimated using an external signal, e.g. a signal acquired by the tracking of markers attached to the scanned object, or during the reconstruction, e.g. by optical flow estimates on the intermediate reconstructed images. Another widely used technique is phase binning. In this approach, the motion is assumed to be periodic and all acquired projection data is ordered in bins according to an externally acquired periodic signal that represents the periodicity in the motion. A reconstruction can then be calculated per phase bin.

The latter has the disadvantage that its quality depends on the number of acquired projections per phase bin. When scanning small animals, the radiation exposure to the animal should be kept as low as possible. These two facts result in the inevitable trade-off between the animal’s total radiation exposure time and reconstruction quality.

However, often there are large regions within the scanned object that remain stationary throughout all phase bins. This extra knowledge can incorporate in the reconstruction algorithm, resulting in comparable image quality with a reduced number of projections. In this contribution, we propose the rSIRT algorithm (region-based Simultaneous Iterative Reconstruction Technique\(^3\)), an algebraic reconstruction algorithm that improves reconstruction quality for phase bin methods. The rSIRT method is demonstrated on a cardiac CT dataset of a mouse.

Method
In this section, the rSIRT algorithm is explained. We assume that 360° projections are available at \(t\) phase bins, from which a dynamic 3D (4D) image can be reconstructed. We refer to \(p_j\) as the projection data associated with the \(j\)th phase bin and define \(p\) as the vertical concatenation of all projection data \(p_1, p_2, \ldots, p_t\).

A standard approach consists in separately reconstructing the 3D images corresponding to each phase bin from the individual projection sets \(p_j (j = 1, \ldots, t)\). We will refer to this approach as the conventional method. It assumes the object to be approximately stationary during the acquisition of projection data in each phase bin. Reducing the radiation exposure to the animal can be achieved by reducing the number of projection images in each phase bin. Unfortunately, this will result in image quality loss when using the conventional method.

However, often large parts of the objects remain stationary while only a limited part is dynamic. For example, if the animal is strapped tightly to a scanner’s couch, a large region within the scanned animal remains stationary throughout the scan. This information can be incorporated in the standard SIRT algorithm\(^1\) in order to improve reconstruction quality, resulting in an algorithm named region-based SIRT (rSIRT)\(^3\). In rSIRT, the time varying reconstruction \(x^{(k)}\) at iteration \(k\) of rSIRT is represented as a collection of reconstructions \(x^{(k)} = \{x_{1}^{(k)}, x_{2}^{(k)}, \ldots, x_{t}^{(k)}\}\). rSIRT starts from an initial estimate \(x^{(0)} = 0\). At the \(k\)th rSIRT iteration, one
SIRT iteration is executed, using the full sinogram \( p \) and \( x^{(k)} \) as an initial estimate. The result of this iteration is set to zero in the changing region. For each part of the sinogram \( p_j \) (\( j = 1, \ldots, t \)), a SIRT iteration is performed and the result is set to zero on the constant region. Finally, these intermediate reconstructions are added to obtain \( x^{(k+1)} = \{x_1^{(k+1)}, x_2^{(k+1)}, \ldots, x_t^{(k+1)}\} \), which serves as initial estimate for the next rSIRT iteration. This method adds more flexibility to SIRT in terms of object dynamics, while still aiming at matching the projection data.

**Experiments**

A cardiac mouse dataset was acquired with a SkyScan 1178 microCT scanner to validate the proposed rSIRT algorithm. It contains projection images of a mouse with beating heart at 515 equiangular directions over a full 360 degree range. At each angle, a total of 20 projection images were captured, each labeled with a time stamp. The cardiac motion was captured independently with an ECG signal. Projections were retrospectively ordered in 5 phase bins according to the periodic ECG signal. If multiple images were assigned to a bin at a certain projection angle, the images were averaged. If no image could be assigned to a bin at a certain projection angle, the projection image of the nearest angular neighbor was assigned to the bin.

Instead of using the full dataset, the projection data on the optical axis is considered and we only maintain 1/5\(^{th}\) of the total data. Define \( \{\theta_i\}_{i=1,\ldots,515} \) as the ordered set of equiangular projection directions. For each phase bin, we selected 1/5\(^{th}\) of the available projection images, defined by the set of angles \( \Omega_j = \{\theta_i \mid \text{mod}(i,5)=j\} \) where \( j \) represents the phase bin index, i.e., \( j=1,\ldots,5 \).

The reduced dataset can be regarded as a dataset obtained with an online synchronization method, where projection images are acquired at time points according to the phase of an external ECG signal. Source and detector were rotated a total of 360° around the object. If \( \theta_i \in \Omega_1 \), an image is acquired at a time point corresponding to the first phase bin, if \( \theta_i \in \Omega_2 \), an image is acquired at a time point corresponding to the second phase bin, and so on. Note that this procedure would expose the scanned animal to only 1/5\(^{th}\) of the radiation that was applied for acquiring the full dataset.

**Results**

In Figure 1, the rSIRT result is compared to the conventional method. For comparing reconstruction quality, we used the SIRT reconstructions on the full dataset, i.e., with 5 bins and 515 projection images per bin. We manually indicated the stationary region as the region within the rib cage and calculated reconstructions using 200 iterations. For now, we only compare reconstructions visually. More quantitative comparison will be performed in the future. From Figure 1, it is clear that rSIRT alleviates streaking artifacts in the stationary region.

Furthermore, it is important to note that the rSIRT reconstruction is more than just an averaging of the stationary region over the different phase-bin-reconstructions with the conventional method. This is illustrated in Figure 2. On the right hand side, the rSIRT reconstruction of the first bin is displayed. On the left hand side, a reconstruction is displayed that was calculated as follows: Starting from the conventional reconstruction (i.e., SIRT reconstruction per phase bin), the average pixel value over all phase bins in the stationary region was calculated. In the variable region (within the rib cage), the pixel values from the conventional reconstruction of the first phase bin are taken. Figure 2 shows a sharper reconstruction in the stationary region for the rSIRT reconstruction. However, not only the stationary region has a sharper reconstruction, also the variable region seems sharper. The reason for this can be found in the fact that rSIRT compares it reconstruction to the projection data at every iteration, hence, when the quality in the stationary region improves, this can have a positive effect on the variable region as well.
Conclusion
This contribution illustrates the ability of the rSIRT method to reconstruct 4D images of comparable quality with respect to conventional methods, using fewer projection data. Using the same amount of data, rSIRT provides improved reconstruction quality in the stationary region. This significantly improves the quality in the variable region as well, since the reconstruction is matched with the projection data in every rSIRT iteration. An additional advantage of the proposed rSIRT algorithm is that it fits in well in current scanner’s design that use the (online synchronized) phase binning technique.

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Figure 1: Comparison of reconstructions. Rows 1-5 correspond to phase bins 1-5. (a) The SIRT reconstruction per bin using the full original dataset. (b) The conventional method’s reconstruction, i.e. the SIRT reconstruction per bin, on the reduced dataset. (c) The rSIRT reconstruction, using the reduced dataset.
Figure 2: Left: rSIRT reconstruction of first phase bin. Right: Reconstruction obtained by averaging the stationary region pixels over all phase bins of the conventional method reconstructions, whereas the variable region is just the variable region of the first phase bin reconstruction of the conventional method. rSIRT has improved sharpness both in the stationary and the variable region.

References: