Editorial

Recent Advances in X-Ray CT Image Reconstruction Techniques

Golshan Mahmoudi [1,2], Hossein Ghadiri [1,2,*]

[1] Department of Medical Physics and Biomedical Engineering, Tehran University of Medical Sciences, Tehran, Iran

[2] Research Center for Molecular and Cellular Imaging, Tehran University of Medical Sciences, Tehran, Iran

Received: 06 September 2019

Accepted: 12 September 2019

DOI: https://doi.org/10.18502/fbt.v6i3.1693

http://FBT.tums.ac.ir

1. Introduction

Advancements in Computed Tomography (CT) have increased dramatically during recent years, offering a more effective non-invasive technique for examining patients without having to resort to exploratory surgeries that were once routine clinical practice. The growing importance of CT as a diagnostic tool increases the need for solutions that improve diagnostic information yet lower radiation to patients. However, these advancements in CT technology are no longer driven solely by hardware components. Software, including reconstruction and image processing, is an important element to diagnostic accuracy. Today, image reconstruction techniques are one of the most important strategies for reducing radiation dose in CT.

Image reconstruction in CT is a mathematical process to build the map of attenuation coefficient, a real-valued function associated with the object of interest, from X-ray measured projection data acquired at different angles around the patient. Generally, image reconstruction algorithms can be divided into two major categories: analytical methods and iterative methods. Below, we will explain CT image reconstruction methods and the corresponding advantages and disadvantages.

2. Image Reconstruction Methods, their Advantages and Disadvantages

Traditionally, CT images have been reconstructed using analytical reconstruction algorithms such as Filtered Back Projection (FBP) because of their simple mathematical computation requirement. In FBP, all of the individual data points for a given detector element (the line integrals representing the total attenuation of the beam as it takes a radial path through the patient) are gathered and projected that piece of information back along the radial path. This is repeated as the tube and detectors rotate around the patient, and the combined attenuation values provided from each of these back projections are summed for each pixel, resulting in the final image. Mathematical filters are applied to the data before back projection to modify image noise and resolution [1].

FBP is fast and simple; however, there are multiple problems with the method. The FBP reconstruction technique is based on many simplifications and assumptions that simplify CT geometry, including the following: the X-ray tube focal spot is an infinitely small point; the detector is also formed of points located at the center of each cell; and the reconstructed voxel is a point with no shape or size. Perhaps most importantly, FBP assumes that the sinogram (the two-dimensional array of data containing the projections) represents a perfect representation of the object being imaged and ignores that the projection data are corrupted by quantum and electronic noise during acquisition and therefore does not

Corresponding Author:
Hossein Ghadiri, PhD
Department of Medical Physics and Biomedical Engineering, Tehran University of Medical Sciences, Tehran, Iran
Tel: (+98) 21 88973653
Email: h-ghadiri@tums.ac.ir

account for image noise and also adds the filtering step amplifies noise to the images. Moreover, X-ray spectra are assumed to be monoenergetic, and nonlinear effects along the assumed ray, for example, scatter and beam-hardening, are not considered in FBP [2].

One way to overcome the overly simplified assumptions of the FBP algorithm is to use a technique called iterative reconstruction (IR). Increased computer processing power has made iterative reconstruction methods clinically feasible. Iterative reconstruction techniques are more demanding compared to FBP but strive to reconstruct CT images with less noise than with FBP, while preserving details and edges. These techniques are aimed at reducing image noise, which both provides improved image quality and enables radiation dose reductions [3].

The underlying approach for the iterative methods is the following. First, a synthesized projection is calculated by performing "forward projection" on images of the estimated object. Basically, this is the first estimate of the attenuation, but with an important difference. These estimate mimics, as much as possible, the process in real CT scanning in which X-ray photons traverse through the object and reach the detector. The synthesized projection is then compared to the real measurement and the difference between the two shows the amount of adjustment or update needed for the current estimation of the object (image). One of the goals of the image update, or modification, is to minimize this difference. This entire cycle continues until the difference between the estimated and measured data is within an acceptable range. While analytical algorithms such as the commonly used FBP are based on only a single reconstruction, iterative algorithms use multiple repetitions in which the current solution converges towards a better solution. As a consequence, the computational demands are much higher. Iterative methods have three major categories: Algebraic Reconstruction Technique (ART), Statistical Iterative Reconstruction (SIR), and Model-Based Iterative Reconstruction (MBIR) [3].

The simplest form of iterative reconstruction is the ART, which was already used for the reconstruction of images in the first CT systems. ART-based methods are non-statistical but model the geometry of the acquisition process better than FBP [3].

Statistical reconstruction methods incorporate counting statistics of the detected photons into the reconstruction process. In transmission CT the number of photons leaving the X-ray tube as well as the measured photons at the detector, which passed through the patient or object, are assumed to be Poisson distributed. The major advantage of SIR techniques involves noise reduction without a corresponding decrease in spatial resolution. SIR algorithms are not computationally expensive or time-consuming to perform clinically on today's computer system. SIR algorithm is sometimes known as a hybrid IR algorithm because of its ability to blend with FBP [3].

While the assumption of the Poisson distribution for photons seems to be valid in most cases, the situation for acquisitions with very low dose is not clear because effects in the detector such as electronic noise are gaining importance compared to the distribution of the photons arriving at the detector and therefore the photon distribution could not be assumed to be Poisson distribution anymore [3].

MBIR, also known as pure IR algorithm, goes beyond modeling statistics of the detected photons as Poisson distributed and has been shown to significantly improve image quality while reducing noise and artifacts. In MBIR, images are reconstructed by minimizing the objective function incorporated with an accurate system model, a statistical noise model, and a prior model. The system model takes into consideration the shape and the size of an X-ray tube focal spot, interaction of the photon beam with the voxel and the three-dimensional shape of detectors. The statistical noise model deals with the nonlinear, polychromatic nature of X-ray tubes by modeling the photons in the measured data set. While the value of modeling the system optics is mainly on the spatial resolution of the reconstructed images, modeling of the system statistics is mainly on the noise of the resulting image. The computational intensity on the modeling of the noise portion of the system is not nearly as big as the modeling of the system optics. The prior model is a regularization algorithm that corrects unrealistic situations during reconstruction to speed up the process. These models are used to predict the volumetric image, with the objective of approximating the actual image as closely as possible and try to model the acquisition process as accurately as possible [4].

However, conventional MBIR algorithms using quadratic regularization term, do not maintain image quality when highly under sampled data are available, because CT image reconstruction from sparse-views (extend sampling interval from a projection with full-coverage) will be a highly ill-posed problem. Compressed Sensing (CS) theory has shown great potential to reconstruct high-quality images from far less measurements than what is usually considered necessary, and also are more robust against under sampled streak artifacts and noisy data [5].

The key point of CS is to design the sparsifying transform which can generate sparse images in which most pixels are zero, and then minimizing the L0-norm of this sparsifying transform. As the L0-minimization is complicated, minimizing the L1-norm is a popular alternative. In CT image reconstruction, the discrete gradient transform is commonly used as a sparsifying transform, and L1-norm of the gradient image is known as a Total Variation (TV) [6].

Despite the great success of the TV method, it has some disadvantages. An image regularized by TV tends to generate blocks with constant grey levels producing artificial edges that are so-called blocky (staircase) effect and is due to the tendency of the TV to arrive at a piecewise constant solution. Another disadvantage of TV is its tendency to uniformly penalize the difference between local neighboring pixels regardless of the image structure, which results in over-smoothing of edges mostly around low contrast regions. Another issue with the TV method is considering only the vertical and horizontal gradient operators, not the diagonal gradients and consequently, some directional information of edges and image texture are lost. Therefore, improving TV the model is highly desirable [7].

3. Conclusion

In recent years, thanks to high performance computers, the application of statistical iterative reconstruction algorithms for reducing dose became feasible in clinical CT. MBIR algorithm is generally superior to FBP and ASIR in areas of radiation dose and image quality. However, MBIR is too slow for clinical use and still is not much used commercially. Therefore, the issues surrounding MBIR will need to be addressed before it is to completely replace the other reconstruction algorithms in CT imaging. Today, deep learning-based image reconstruction techniques have become a new frontier in sparse-view CT image reconstruction. Combining reconstruction techniques that have been developed in a long history with the deep learning will make a breakthrough in CT image reconstruction field.

References

1- J. W. Nance, U. J. Schoepf, and U. Ebersberger, "The Role of Iterative Reconstruction Techniques in Cardiovascular CT," *Curr Radiol Rep*, journal article vol. 1, no. 4, pp. 255-268, December 01 2013.

2- R. Schofield *et al.*, "Image reconstruction: Part 1 - understanding filtered back projection, noise and image acquisition," (in eng), *J Cardiovasc Comput Tomogr*, Apr 16 2019.

3- M. Beister, D. Kolditz, and W. A. Kalender, "Iterative reconstruction methods in X-ray CT," *Phys Med*, vol. 28, no. 2, pp. 94-108, 2012.

4- L. Liu, "Model-based Iterative Reconstruction: A Promising Algorithm for Today's Computed Tomography Imaging," *J Med Imaging Radiat Sci*, vol. 45, no. 2, pp. 131-136, 2014/06/01/ 2014.

5- H. Qi, Z. Chen, J. Guo, L. J. B.-m. m. Zhou, and engineering, "Sparse-view computed tomography image reconstruction via a combination of L 1 and SL 0 regularization," vol. 26, no. s1, pp. S1389-S1398, 2015.

6- D. L. J. I. T. o. i. t. Donoho, "Compressed sensing," vol. 52, no. 4, pp. 1289-1306, 2006.

7- G. Mahmoudi, M. R. Fouladi, M. R. Ay, A. Rahmim, and H. Ghadiri, "Sparse-view statistical image reconstruction with improved total variation regularization for X-ray micro-CT imaging," *Journal of Instrumentation*, vol. 14, no. 08, p. P08023, 2019/08/27 2019.

