Final Term Paper

Title : Iterative reconstruction in low dose CT with Artificial Neural Network

1. Introduction

Computer Tomography Imaging(CT) has proved to be a significant tool in radiology in making complex clinical decisions about physiology and anatomy of living organisms. Since its introduction in 1900's, it has undergone various developments in this technology to dig deeper into the radiology imaging world.

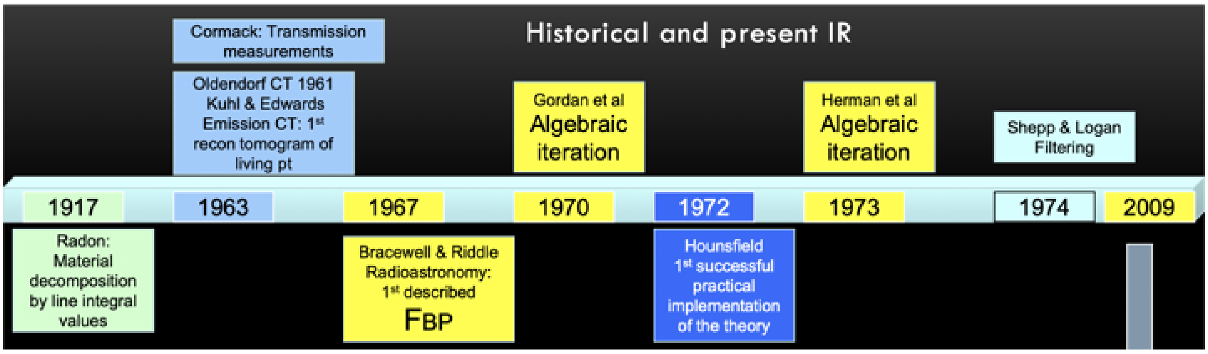
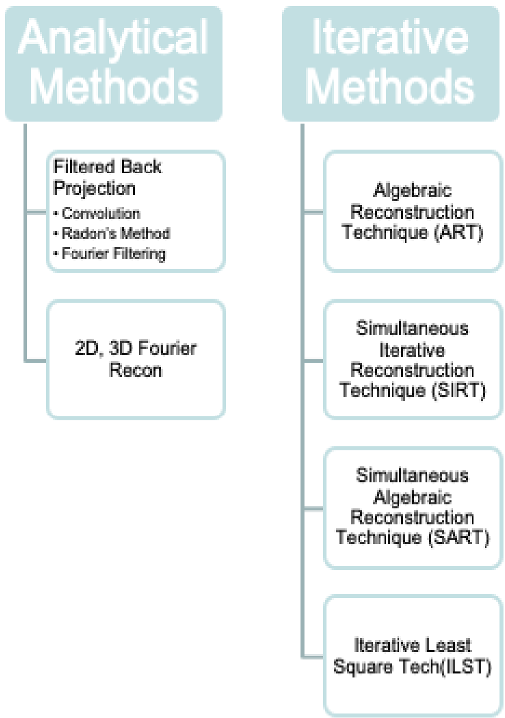


Fig 1: Timeline of the advancements in CT imaging.[9]

CT is the most frequently used imaging modality after X-ray and the proclivity is due to its noninvasive, fast, painless procedure. A CT examination can provide identification of injuries in all the internal organs, guide biopsies, assist in the pre and post surgery procedures, administration in radiation therapies, bone mineral density, among the wide clinical applications that CT has[1]. This has resulted in growing demand to produce accurate, high resolution, fast resulting, low dose, low radiation exposure CT imaging. The images here are formed due to the attenuation coefficient of the tissues and as a result, contrast in the image is produced. To summarize the basic, tomographic image is a result of reconstruction from its projection data. Apart



from this, it has widely been used in non-medical applications[2]. As a result, it attracted lot of research interest and gave rise to various methodologies

There two types of methodology for reconstructions- 1) Analytical and 2) Iterative. In the former, transform based methods are used to reconstruct the image. It requires a large number of projections and projections that are uniformly distributed over 180 or 360°. It also does not address the issues of refraction and attenuation that the propagating rays undergo. Iterative reconstruction on the other hand was the solution to this.

The iterative reconstruction method was introduced in the early 1970s. It is a technology that assumes an image space and then sets up algebraic equations for the unknown in terms of the measured projection data by devising iterative procedures to adjust and reconstruct the image. As the definition suggests, it involves high mathematically calculations and computational power both of which were meager when the concept was initially executed by the industry stalwart Godfrey Hounsfield[3]. 3 categories under Iterative methods are largely studied- 1) ART 2) SART 3)SIRT.

2. Concept

2.1 Algebraic Reconstruction Technique

This concept was first introduced by Gordan, Bender and Herman[5]The basic principle can be explained by starting with the superposition of a square grid(NxN) over an unknown image whose values are assumed to be constant[4] [Fig 2].

'f_i' is a one dimensional vector of n elements each representing a voxel value of a certain volume and 'p_i' gives the one-dimensional vector of n elements and each element represents a measurement taken at a certain detector in a certain projection direction. 'w_{ij}' is an NxN projection matrix and is a volume geometry to a certain projection geometry.

$$\sum_{j=1}^{N} w_{ij} f_i = p_i \tag{1}$$

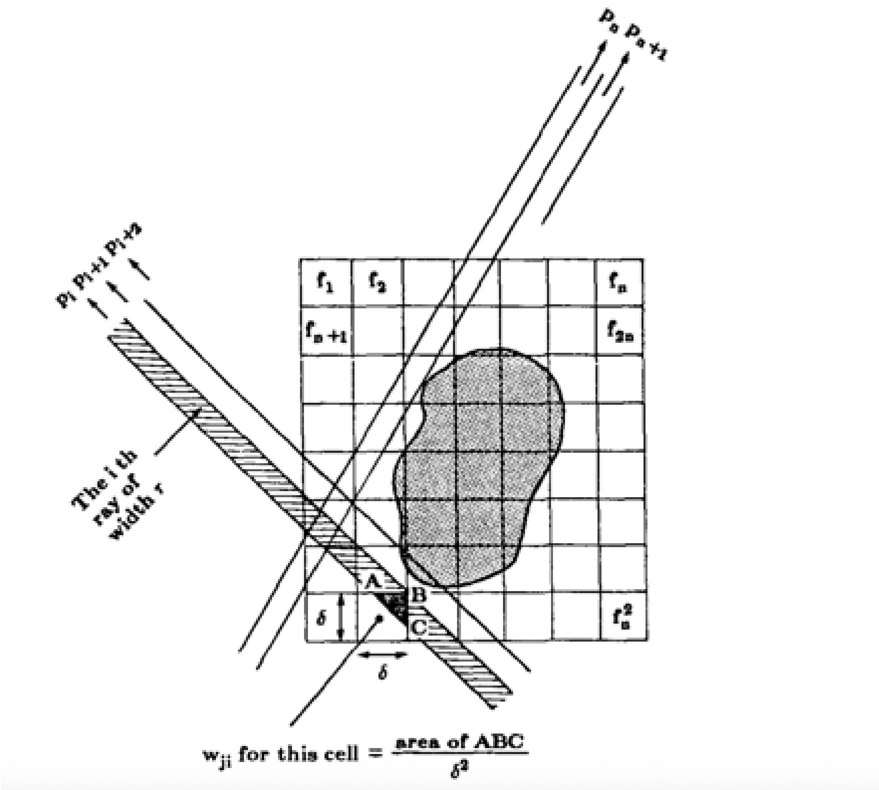


Fig (2) : Object overlapped with square grid with NxN grids.[4]

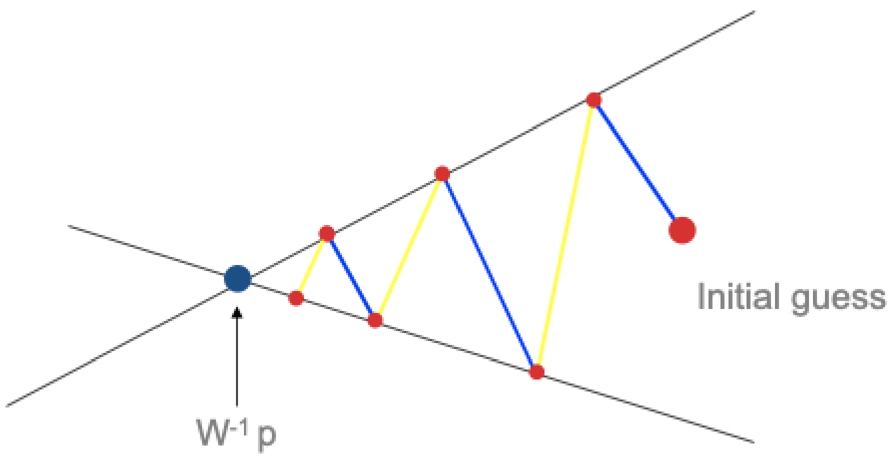
By using conventional matrix theories, we can solve the system of equations(1)[4] to map the projection data and obtain the image data. But in practical applications, images are of the size 256x256 or higher. For such cases, N can get as large as 65,000. For 'w' matrix computations, direct matrix inversions to obtain the image can get challenging especially when there is possibility of noise.

The solution was to come up with an optimisation problem where the solution vector can be found such that the difference between the measured projection data and simulated projection of the solution is minimal in some norm. The concept was first proposed by Kaczmarz and Tanabe and is based on "iterative methods of projection"[4]

$$f^{(i)} = f^{(i-1)} - \frac{(f^{(i-1)}.w_i - p_i)}{w_i \cdot w_i} w_i \tag{2}$$

For the reconstruction application, an initial guess of the solution is taken denoted by f(0). This is then projected on the vector hyperplane to obtain f(1). The process is repeated until it converges to yield f(i). This process is defined by the mathematical equation (2) and can be rewritten for implementation in 2D image space as

$$f_j^{(i)} = f_j^{(i-1)} + \frac{p_i - q_i}{\sum_{k=1}^{N} w_{ik}^2} w_{ij} \tag{3}$$



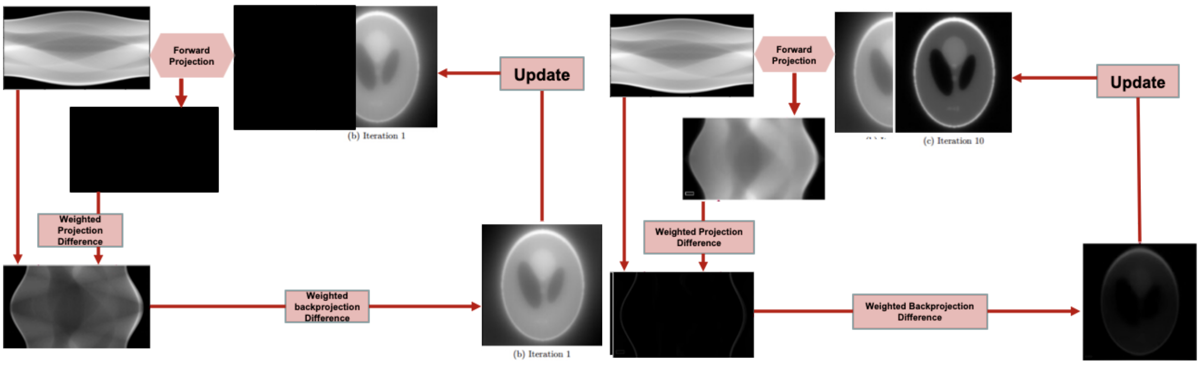
Fig(3) : A depiction of how initial guess arrives at the original value

ART methodology only updates a single measurement with each iteration and SART method updates all measurements of a single projection in each iteration. This methodology can exhibit noisy salt and pepper characteristics[6] and potentially pose inconsistencies in the forward process equations.[4]

2.2 SIRT

This methodology is more advanced in terms of updating all measurements of two or more projections in each iteration.

$$f^{(1)} = f^{(0)} + CW^T R(p - Wf^{(0)}) \qquad f^{(10)} = f^{(9)} + CW^T R(p - Wf^{(9)})$$



Fig(4): Overview of the iteration cycle-A: After 1 iteration, B.After 10th iteration

$$f^{(k)} = f^{(k-1)} + CW^T R(p - Wf^{(k-1)})$$

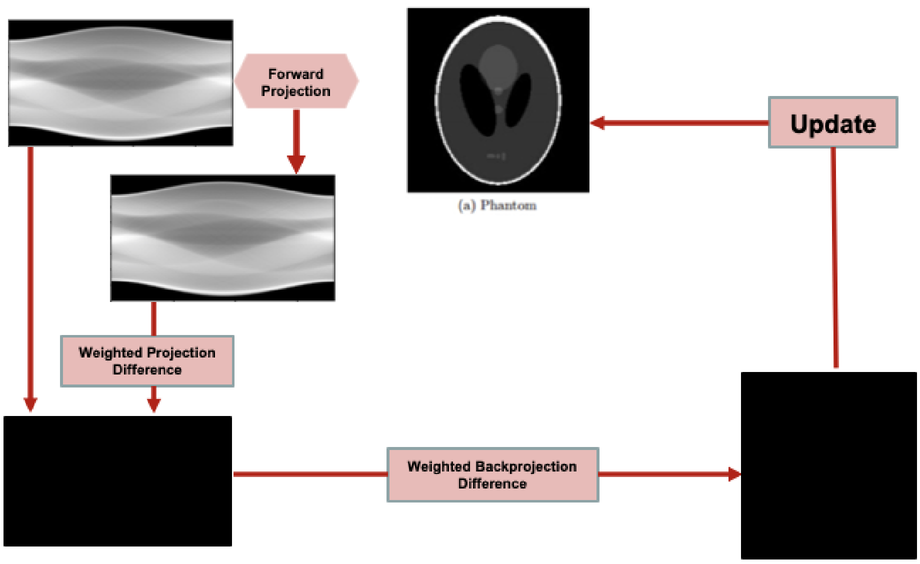


Fig (5) . SIRT Reconstruction resulting in final phantom image after k^{th} iteration

The task starts with an initial volume f(0) which is typically a blank image that we assume which is forward projected with a sinogram of a phantom. This gives a blank sinogram and when subtracted from the measured sinogram projection, we obtain a weighted projection difference which is again back projected to obtain the phantom image. First iteration results in a blurry image but for 10 iterations, we observe more definition in the obtained phantom with weighted projection difference and weighted back projection difference almost reaching a null. If we keep on iterating for about 100 iterations, we converge to the original phantom image as shown fig(5). Least square methods aid in converging the reconstructed images faster compared to the above methods but requires more data storage space.

3. Comparison to other CT imaging methodology

3.1 Advantages

When we look into the basic properties of the Filtered Back Projection method which is an Analytical approach for reconstruction, the integrals are measured at each detector for a particular angle of projection. The projection data is fourier transformed and multiplied by the weighing function. Then the back projection process involves calculating the inverse fourier transform of the filtered projection[4]. The filter jeopardizes the spatial resolution and image noise. If the parameters of the filters are modified to obtain a sharper image, then we see an increase in image noise. Also a major bottleneck is the image noise that occurs due to poisson distribution variations in photon number. Another drawback in FBP is the radiation dose which is a huge trade off to image noise. Higher image noise impacts the clinical decisions due to its interference in delineation and contrast of the image.[7]

Hence the deployment of the IR algorithm had two main motivations - reduction in noise and dosing.

Firstly, addressing the main goal is it has a better insensitivity to noise as the algorithm gets down to each voxel and error correction is done in each iteration. It reduces the noise with no impact on spatial or contrast resolution. Figures 6 (a) and (b) depict how IR methodology produces images with high resolution and good comparable SNR and CNR against the FBP methods.

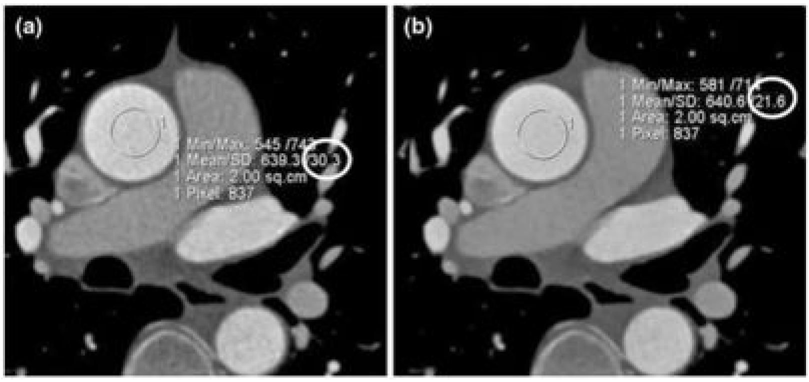
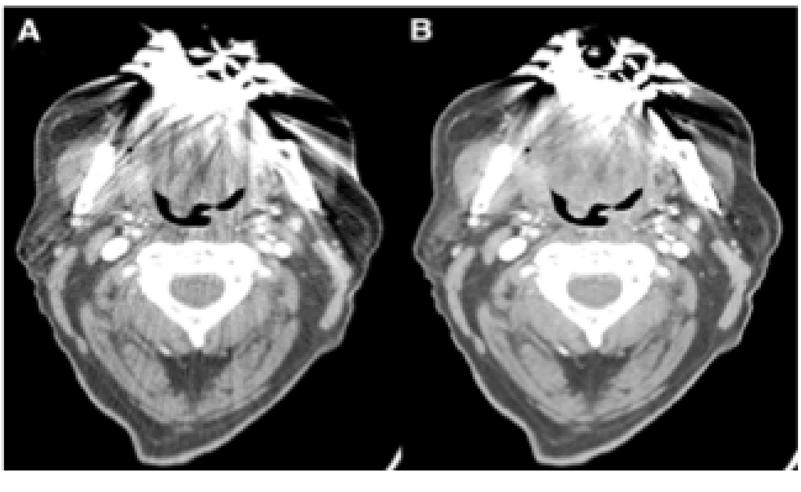


Fig (6). Image (a): FBP has high standard deviation of attenuation depicting higher image noise. Image (b): Image reconstructed with IR algorithm shows lower SD of attenuation with better resolution.[7]

Further, it can achieve optimal reconstruction with limited data or if part of the data is missing unlike in the case of FBP where every projection data counts for final image reconstruction. It is also observed to help overcome problems when the projection data are not uniformly distributed in angles in case of the fan beam projections. It is also instructive in applications of artifact suppression. In many clinical applications, imaging a subject with stent, dental wear or any hardware installed in the body, it becomes challenging to deal with the possibility of the alterations in radiation.



Fig(7) : A. FBP with metallic artifacts caused by dental hardware.B. Reduction in metallic artifacts with IR algorithm[7]

Secondly, addressing the 2nd shortcoming in FBP method, IR algorithms employ low radiation dose without affecting the noise or compromising resolution of the image.[8]

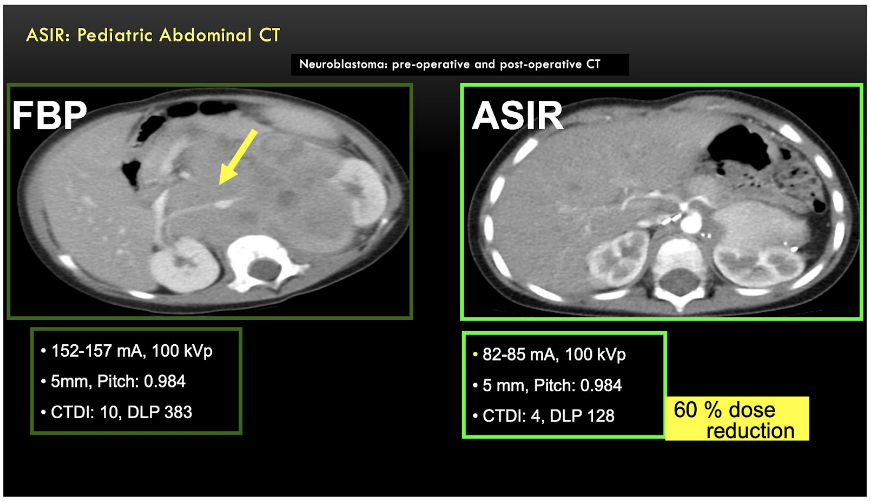


Fig (8) : A pediatric abdominal CT showing 60% dose reduction with IR acquisition on the right when compared to FBP acquisition on the left.[9]

This characteristics of IR can be applied to pediatric diagnosis, where high radiation exposure is one of the main concerns. In general, advances in IR has drastically reduced radiation exposure in commons to harmful high doses of X-rays.

3.2 Disadvantages

The IR acquisition aimed to reduce noise in the image is also susceptible to losing important information sometimes. In fig(9), we observe that a possible lung fissure goes undetected when the dose levels are reduced in IR. Whereas, in FBP acquisition, the lung fissure structure is detected but with higher radiation dose. The reconstruction times are longer compared to FBP owing to mathematical computations. For over 50 years, FBP methodology has been applied and well established in the industry. Replacing advanced technology like IR may come with high expenses and can face high replacement costs.

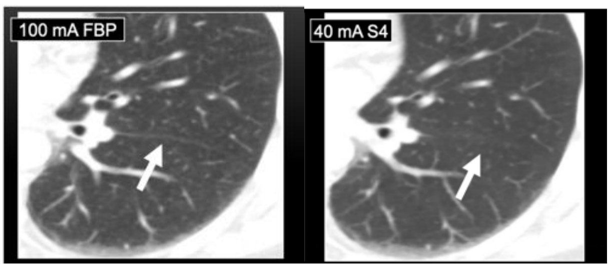
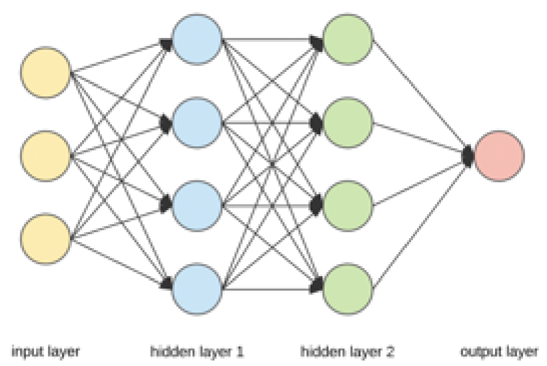


Fig (9): A. FBP with higher dose.

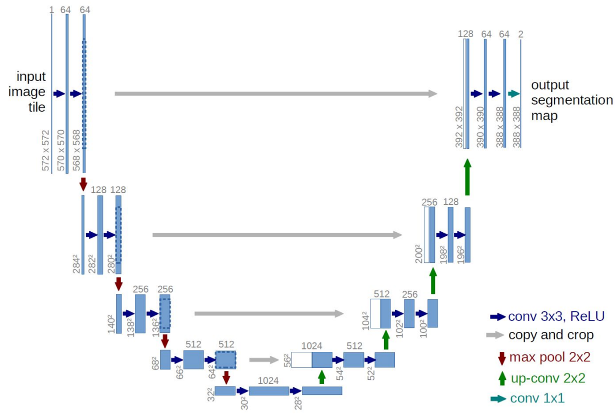
B. Missing lung fissure with low dose IR.[9]

4. Artificial Neural Network

This concept is inspired from biological neural networks and is implemented in a computing system. The Artificial Neural Network basically consists of 3 layers(Image Source) 1) Input Layer 2) Hidden Layers for computation 3) Output Layer. The learning process takes place with 2 steps 1) Forward- Propagation where the network tries to approximate an answer and 2) Back- Propagation is where the error is minimised between the approximated answer and actual answer. We observe how this process resonates with the function of an IR acquisition method. In addition to this, ANN has more complex computations with weights added in the hidden layers known as “biases”. The hidden layers map the features of the underlying function of the given data and biases help in improving the function to match the original function.[12]



With the introduction of high computational power and GPU’s, we now have the ability to perform these computations to arrive at the result. And hence we’ve seen artificial intelligence take off in the imaging domain. With millions of medical imaging data produced every year around the world, this upholds the power of data and more possibility to improve the current technology with integration of AI science in the medical field. A lot of the shortcomings we see in IR methodology is seen to be ameliorated with AI networks such as 1) ResNet 2) Autoencoder 3) UNet and 4) FBP based residual network[10]



UNet(Image Source) especially has been a popular network to work with images and from a typical flow diagram of UNet with downsampling and up sampling, features are mapped onto latent space that follows a certain distribution and then it reconstructs the data from that latent space[11] Another approach was using directional wavelet transform method to extract the directional component of the artifacts and suppress the CT image noise[13] K-sparse autoencoders were shown to reconstruct from low dose CT images[14] In terms of industry implementation, AI methodology involves estimating a lot of image components with predictions and hence cannot be completely reliable. But with deeper layers, more features can be extracted. With lot of research work coming out, FDA has now issued a discussion document and possible regulatory framework for the companies intending to integrate AI into medical diagnosis.[15][16]

5. Conclusion

All in all, IR has more advantages when compared to other reconstruction methods and is currently highly considered. It has a lot of scope in terms of integrating newer methodologies to the existing technology. For example, every company in the industry has their own IR algorithm with its own workflow and settings. It can also be applied to other imaging modalities like SPECT, PET, MRI etc. Finally to conclude, IR methodology integrated with AI is a possible future considering how deep learning can correspond with the shortcomings of iterative reconstruction.

References :

1. Computed Tomography (CT) - Body. (April 10, 2018). Retrived from - https://www.radiologyinfo.org/en/info.cfm?pg=bodyct

2. van Kaick, G., Delorme, S. Computed tomography in various fields outside medicine. *Eur Radiol Suppl* 15, d74–d81 (2005). https://doi.org/10.1007/s10406-005-0138-1

3. Iterative Reconstruction 101. (July, 2013). Retrieved from - https://www.itnonline.com/article/iterative-reconstruction-101-0

4. A. C. Kak and Malcolm Slaney, *Principles of Computerized Tomographic Imaging,* Society of Industrial and Applied Mathematics, 2001

5. R. Gordon et al., “Three-Dimensional Reconstruction from Projections: A Review of Algorithms”, International Review of Cytology, Vol. 38, p. 111 (1974)

6. Andersen, A. H., & Kak, A. C. (1984). Simultaneous Algebraic Reconstruction Technique (SART): A Superior Implementation of the Art Algorithm. *Ultrasonic Imaging*, *6*(1), 81–94. https://doi.org/10.1177/016173468400600107

7. Lucas L. Geyer, U. Joseph Schoepf, Felix G. Meinel, John W. Nance, Jr, Gorka Bastarrika, Jonathon A. Leipsic, Narinder S. Paul, Marco Rengo, Andrea Laghi, and Carlo N. De Cecco, State of the Art: Iterative CT Reconstruction Techniques, Radiology 2015 276:2, 339-357

8. Justin Solomon, Daniele Marin, Kingshuk Roy Choudhury, Bhavik Patel, and Ehsan Samei, Effect of Radiation Dose Reduction and Reconstruction Algorithm on Image Noise, Contrast, Resolution, and Detectability of Subtle Hypoattenuating Liver Lesions at Multidetector CT: Filtered Back Projection versus a Commercial Model–based Iterative Reconstruction Algorithm, Radiology 2017 284:3, 777-787, Feb 7 2017, https://doi.org/10.1148/radiol.2017161736

9. Iterative reconstruction: Does it Work to Reduce Noise Without “Messing” up the Images? By Sarabjeet Singh, MD, MMST Lecturer of Radiology, Harvard Medical School Assistant to Research, Department of Radiology Massachusetts General Hospital. Retrieved from- https://www.aapm.org /meetings/2013CTS/documents /FRI_ 03Singh . ARS.pdf

10. Zhang, H., Dong, B. A Review on Deep Learning in Medical Image Reconstruction. *J. Oper. Res. Soc. China* (2020). https:// doi.org/10. 1007/s40305-019-00287 -4

11. Na Lei, Dongsheng An, Yang Guo, Kehua Su, Shixia Liu, Zhongxuan Luo, Shing-Tung Yau, Xianfeng Gu, A Geometric Understanding of Deep Learning, Engineering, Volume 6, Issue 3, 2020, Pages 361-374, ISSN 2095-8099, https://doi.org/10.1016/j.eng.2019.09.010.

12. Basics of Neural Network, Apr 3, 2018, Retrieved from- https://becominghuman.ai/basics-of-neural-network-bef2ba97d2cf

13. Kang E, Min J, Ye JC. A deep convolutional neural network using directional wavelets for low-dose X-ray CT reconstruction. Med Phys. 2017 Oct;44(10):e360-e375. doi: 10.1002/mp.12344. PubMed PMID: 29027238.

14. D. Wu, K. Kim, G. El Fakhri and Q. Li, "Iterative Low-Dose CT Reconstruction With Priors Trained by Artificial Neural Network," in IEEE Transactions on Medical Imaging, vol. 36, no. 12, pp. 2479-2486, Dec. 2017, doi: 10.1109/TMI.2017.2753138.

15. US FDA Artificial Intelligence and Machine Learning Discussion Paper. Retrieved from- https://www.f da.gov/files/medical%2 0devices/published/U S-FDA-Artificial-In telligence-and-Machine-Learning-Discussion-Paper.pdf

16. https://www.fda.gov/medical-devices/software-medical-device-samd/artificial-intelligence-and-machine-learning-software-medical-device