An Empirical Study of Tomography and Denoising Algorithms

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Abstract : Current technology makes enormous impact in electron tomography. The field of transmission electron microscopy (TEM) has received significant growth and advantage in modern equipment such as field-emission electron arms, aberration correctors and monochromators. The proposed methodology extends the traditional filtered back projection by applying ramp filter which is applied in Fourier transform domain. The value of reconstructed image is formed by dot-product of the discrete projection data with the weight vector. The reconstruction image has been converted back by modified filtered back projection method using ramp filter with inverse discrete Fourier transform is computed for each of the projection data, reconstructed data is computed by dot product of above computed data and ramp filter. The performance of the reconstruction technique is analyzed in terms of various measures and tested using various indicators such as mean square error and results obtained indicates that proposed methodology performs significantly better than traditional analytical reconstruction methods.

***IndexTerms* - Tomography, Discrete Tomography, Total Variation Regularized Discrete Algebraic Reconstruction Techniques, Compressed Sensing.**

I. INTRODUCTION

Tomography reconstruction is a form of multidimensional inverse problem in which the task is to provide an approximation from a limited number of predictions of a particular system. A noteworthy example of uses is Computed Tomography (CT) reconstruction, in which cross-sectional photographs of patients are collected in a non-invasive way. Recent advances have seen the Radon transform as well as its inverse use for tasks linked to practical placement of artifacts needed to assess and evaluate the use of computed tomography in airport health [1-4].

Practical techniques for the reconstruction of a 3-dimensional object from its projections were built to automate the procedure. Such algorithms are built primarily on the basis of the Radon Transform mathematics, statistical awareness of the mechanism of data acquisition, and computer imaging device geometry. Denoising is among the essential image processing functions in reconstruction of objects. Automatic elimination of the noise may increase the diagnostic quality and involves careful handling of the image collected. This paper studies various tomography algorithms and fine tuning of parameters to reduce noise [6-10].

II. TYPES OF TOMOGRAPHY

a) Computed Tomography

In Computerized tomography uses as X-ray as imaging technique to capture the cross section of the object at various angles. Generated signals are further processed by computer to generate image.

b) Electron Tomography

It is technique that captures the projection of the object through electron microscope and uses these projections to reconstruct the object.

c) Wide angle Tomography

In this technique, object with complete obscurity by overlying shadows in radiograph. Slice thickness becomes thin, when the exposure angle is wide. It is generally applied in very thin section and there is no thickness between the adjacent parts of the image.

d) Zonography

This technique is also known as narrow angle tomography. It requires multidirectional tube motion rather than linear tomography. It is generally used for objects especially useful for tissues which have little natural contrast.

e) Circular Tomography

In this technique, movement of x-ray focus path to the movement of tube and always parallel to the base of image, which can produce uniform section thickness. All portion of phantom image are uniformly blurred.

f) Skip Tomography

In this technique, it stops the exposure through certain angle or portion of tube's motion. It is generally used where there is a substantial difference between the object of interest and object to be blurred.

g) Multisession Tomography

In, several areas of film are recorded during single topographic swing. There exists a single mechanical fulcrum for top film and virtual exits for every other film. Top and every other film are equally magnified

III. TOMOGRAPHY ALGORITHMS

In several scientific findings, X-ray computed tomography (CT) plays a key role. Reconstruction of X-ray CT images is an exciting computational and mathematical problem. Iterative reconstruction algorithms are becoming increasingly popular due primarily to the recent surge in computational power. This segment provides a brief description of the tomography algorithms used in X-ray CT [11-18].

Fourier-Domain Reconstruction Algorithm

Using interpolation, reconstruction can be performed. Assuming f(x,y) N projections are created at spaced evenly angles, each sampling at the same speed. The Discrete Fourier transform will give sampling in the frequency domain on each projection. In the frequency domain a polar raster would be created by integrating all the frequency-sampled predictions. The polar raster will also be sparse so interpolation is used to fill the unidentified DFT points and reconstruction can be achieved by inverse Discrete Fourier transformation. Reconstruction efficiency can be improved by developing methods to adjust the sparsity of the polar raster, thereby promoting interpolation efficacy.

For example, in the frequency domain, a linear motion square raster can be produced by modifying the angle across each projection as follows:

$\Theta' = R_o / \max\{|\cos\Theta|, |\sin \Theta|\}$

where R_o is the highest frequency to be evaluated.

The focused square raster increases operational performance by enabling all rectangular DFT lattice interpolation locations to be on. It also has a growing interpolation error. Yet the Fourier-Transform algorithm has an extremely noisy performance drawback.

Back Projection Algorithm

In the study of reconstruction of tomography images, a balanced and discrete variant of the inverse Radon transform is sometimes used, recognized as the filtered back projection method. The inverse Radon Transform is the angular distance between the projections, for a sampled discrete system which is shown in Fig. 3.1.

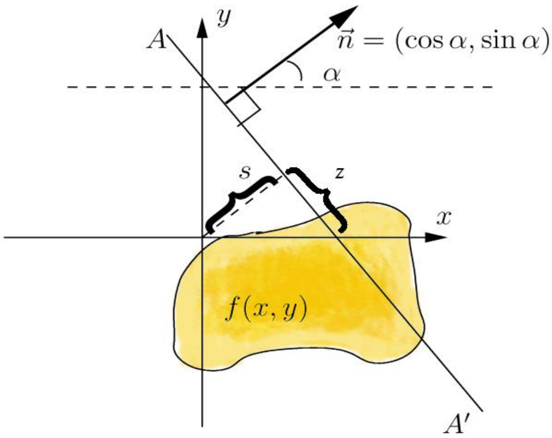

Fig. 1 Inverse Radon Transform

The term back-projection lies in the fact that in addition to get a 2D signal, 1D projection has to be processed by 1D Radon kernel (back-projected). The filter itself does not include DC gain so it would be beneficial to incorporate DC bias. Using back-projection reconstruction provides better resolution than the interpolation approach mentioned above. Nevertheless, since the filter is likely to intensify high-frequency material it produces greater noise.

Iterative Reconstruction Algorithm

The iterative reconstruction applies to iterative algorithms used in some imaging techniques to recreate 2D and 3D images. For example, an image from an object's projections must be recovered in computed tomography. Iterative reconstruction strategies here are typically better, but more costly in computational terms Compared to the popular filtered back projection method (FBP) which determines the image directly in a single reconstruction step. In current research works, researchers have shown that it is possible to recreate iteratively extremely fast calculations and massive parallelization, which makes iterative reconstruction feasible for commercialization.

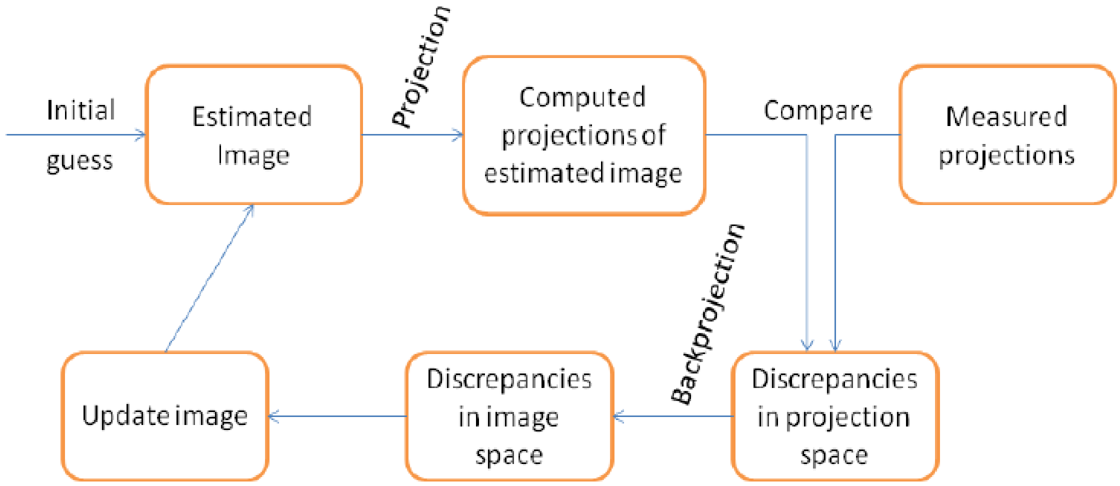

Fig. 2 Illustration of Iterative Reconstruction Process

Procedure

Input:

A standard filtered back projection algorithm is used to create a primary image using the raw data produced by the computed tomography scanner as shown in Fig. 2.

Image Reconstruction Loop:

- A forward projection to the primary image creates artificial raw data,
- The simulated data is then compared with the raw data measured when an updated image is produced, and then
- A filtered back projection is used to back-project the current image to the newly modified image; this is repeated until the image discrepancies exceed a pre-set value.

The benefits of the iterative method include enhanced noise insensitivity and the potential to recreate an optimal picture in the event of missing results. The approach has been implemented in modalities of emission tomography such as SPECT and PET, where substantial attenuation occurs along ray paths and there is fair low noise statistics.

3.3.4 Fan-Beam Reconstruction

The use of such a non-collimated fan beam is popular, as it is difficult to acquire a collimated radiation beam.

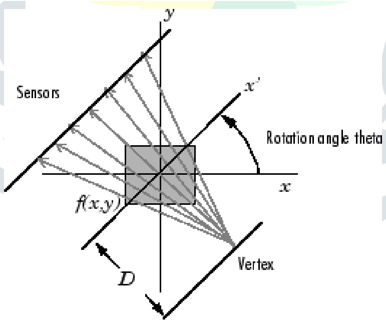

Fig. 3 Fan- Beam Reconstruction method

Fig. 3 shows ss estimates, fan beams produce series of line integrals, not parallel to one another. The fan-beam system may involve a range of angles of 360 degrees which imposes mechanical restrictions, but enables for faster signal acquisition times which may be beneficial in certain situations. Back projection uses a similar two-step method, which results in reconstruction by calculating weighted sum back projection from filtered projections.

The method calculates image matrix projections along given directions. A two-dimensional vector projection f(x,y) is a set of integrals of the axis. The fan beam function calculates line integrals along paths radiating from a single source, creating a shape of a fan. The fan beam method takes several projections of the image from different angles to reflect an image by rotating the source around the image centre. The following Fig. 3.3 represents a projection of a single fan-beam at a given rotation angle.

Deep Learning Reconstruction

Deep learning techniques are usually applied to image reconstruction through and remarkable results were obtained in various image reconstruction tasks like low-dose denoising, sparse-view reconstruction, small angle tomography and reduction of metal objects. To accomplish image-to-image reconstruction, one class of deep learning reconstruction algorithms implement post-processing neural networks, where input images are replicated using traditional reconstruction approaches.

An example application is object reduction using the U-Net as done by Matteo Ronchetti et.al (2020) in a small angle tomography. Though, in an image reconstructed by this fully data-driven process, inaccurate structures that occur. As defined in the principle of precision learning, the incorporation of established operators into the architecture design of neural networks thus appears beneficial. For instance, it is important to learn direct image reconstruction from the projection data from the distorted back-projection method. Another illustration is through the unrolling of iterative reconstruction algorithms to create neural networks. Except for accurate learning, using traditional methods of reconstruction with a prior deep learning reconstruction is also an alternative approach to improving image quality.

IV. STUDY OF DENOISING ALGORITHMS IN TOMOGRAPHY

Although X-ray Computed Tomography (CT) allows the ultra-fast acquisition of patient images acquired with excellent spatial resolution, the dose required to reach the diagnostic image quality will result in a significant incidence of cancer development. The low-dose CT imaging is also clinically needed and has been under review for many years. Reducing the radiation dose can completely undermine diagnostic performance or undermine the confidence of doctors by generating noisier images. Several various computational methods were suggested to reduce noise effects in CT images, including denouncing projection data, improving reconstruction formulas to provide noise statistics, and denouncing CT picture [19-24].

For X-ray projection results, the major source of noise is quantum noise induced by numerical variations for X-ray quanta entering the detectors, so that the CT projection noise matches the Poisson distribution. Nonetheless, the noise levels of the processed CT images are normally uncertain due to the use of various reconstruction methods and signal processing measures in CT reconstruction and are hard to model and are spatially changing. In addition, in many CT images, spatial noise in the form of streak artifacts is present. Consequently, it can be very difficult to integrate reliable noise statistics into image-based CT denoising. Many problems occur when denoising is based on data from the forecast and its statistics. These denoising approaches and the related iterative reconstructions explicitly require access to the actual CT data, which is often impossible. In addition, these methods have a high parallelization which makes it difficult to acquire a final image in a reasonable amount of time, based on the available computing resources. At the other hand, image-based denoising approaches are swift and can be easily transferred to CT images without altering the workflow of clinics.

A simplified noise model is typically used in image-based denoising algorithms, in which the final noise in each voxel assumes a Gaussian distribution following the Central Limit Theorem (CLT). The CLT can be used, because in CT images each voxel is determined by inserting values from several different projections. With this definition, a noisy CT image can be described by $y=x+n$ where x is the noiseless image and n is a zero-mean additive anisotropic Gaussian noise with a variance of $\sigma^2 n$, which varies with the position and value of the pixels.

Computer tomography (CT) and X-Ray imaging devices use X radiation to take images, which are typically distorted by a Poisson distribution accompanying noise. Because of the importance of eliminating Poisson noise in medical imaging, several state-of-the-art approaches have been reviewed in the research on the processing of images. These include approaches focused on regularization of Total Variation (TV), wave-lets, key component analysis, machine learning and so on.

The aforementioned significant Poisson removal approaches are used to denoise: the adapted TV model-based method, the innovative TV method, the evolutionary non-local total variation method, the greater-order natural image prior model-based technique, the Poisson bilateral filter reduction method, the PURE-LET method, and the variance stabilizing transform based models.

Different denoising methodologies based on images were used to calculate noiseless CT images, such as anisotropic diffusion, total variation (TV), bilateral filtering, or wavelet-based methods. These methods can normally be developed as a problem of unconstrained Lagrangian multiplier optimization. To interrupt the TV iterations, the statistical features of the high frequency wavelet sub bands were utilized. These approaches, however, cannot distinguish from well-denoted data over smoothed data. As a consequence, the updating steps are usually chosen to be small to prevent over-smoothing, which reduces the convergence speed.

Previously, non-local patch dependent algorithms have been shown to exceed others in denoising CT image. For instance, a non-local means (NLM) based method, which takes control of the existence of repeating constructs in a given image, was contrasted with a denoising method centred on theory component analysis and a highly restricted back projection method. The NLM approach has been shown to exceed all methods in terms of noise contrast ratio, noise standard deviation and squared error.

A further class of methodologies in the whole 2D image makes it look for similar blocks and stacks them together during 3D arrays. Denoising is then done by shrinking the 3D arrays from the transform domain. Such 3D patches are used by an algorithm called K-SVD to train an optimal dictionary. This system, which implies that the trained dictionary atoms can sparsely reflect any 3D fragment, uses shrinkage equations to denoise the patches.

Digitization is now an essential strategy for enhancing image quality in medical imaging systems and attention must be given to the Poisson noise properties in order to effectively eliminate it. Because Poisson noise is a form of signal-dependent noise, it is inadequate to apply the normal denoising approaches such as for additive noise. The method that has been extensively studied over the past couple of years and is winning several distinctions is regularization by absolute variation. This method is based on the much-developed regularization.

To eliminate noise on digital images, the complete variation regularization is used. In essence, they reduced a functional energy centred on L2 image gradient norm with fixed noise variance restriction. The model suggested was also known as the ROF model (Rudin-Osher-Fatemi). The work is well established and has been cited tens of thousands of times. How-ever, the ROF model relies on preserving images that Gaussian noise degrades. This design is inadequate in processing Poisson noise: The edge is not well maintained in the resulting image; If the regularization force decreases, the noise persists in a higher intensity-region.

To address the ROF model's shortcomings, an updated version is suggested that can handle the Poisson noise well. This model is called the Modified ROF (MROF) model. Though, both original methods which are based on ROF and MROF have an effect artificial object. The objects on digital images are misrepresentations of processing images. This influence makes pictures seem alien to certain regions. There are several types of artifacts, such as: staircase, star, halo etc. Those objects may cause doctors to misinterpret actual pathology in medical imaging. We typically have to learn to recognize these artifacts in order to prevent errors. Therefore, these artificial regions should not be generated during processing. To avoid this impact an adaptive version of MROF is suggested. This approach is recognized as the Adaptive Total Variation (ATV) approach.

A common issue with both MROF and ATV methods is that processing on photon-limited images is inefficient. The non-local PCA method is suggested to improve quality of this form of image in denoising process. Subsequently, another non-local adaptive total variation approach (ANLTV) is suggested. This method improves the image information structure and offers photon-limited images a great denoising result.

Non-local solutions such as ANLTV are cutting-edge. Though, if the local models are coupled with the training cycle, we can obtain the outcome can be obtained that is not inferior to other state-of-the-art non-local models. It is proposed that a local variation model integrates the areas of expert prior image that are commonly used in image prior and regularization designs. This method is classified as the naturally occurring higher-order picture prior model (HNIPM). On high and low peak pictures the HNIPM can suppress Poisson noise. While this model becomes local because the model is conditioned on the Anscombe transform domain (very good for Poisson denoising), compared to other state-of-the-art Poisson denoising methods it is also a competitive model. Though, above approaches are implemented on iteration and this involves more execution time to eliminate noise.

A spatial domain filter is suggested to eliminate Poisson noise by changing the bilateral filter structure. The bilateral filter reduction Poisson (PRBF) is non-iterative in character. So, Poisson noise can be handled better than iterative based strategies. Another solution-wavelet and its modifications-is highly predicted. A denoising approach focused on image-domain minimization of Poisson's unbiased risk assessment is addressed: PURE-LET (Poisson Unbiased Risk Estimation – Linear Threshold Expansion).

In a converted domain, this procedure is performed: undeci-mated discrete wavelet transform and can be expanded with some other transforms. It is proposed that a multi-scale stabilizing transform variance (MS-VST) be considered an application of Anscombe transform. May also integrate this transformation with wavelet, ridgelet, and curvelet. Both PURE-LET and MS-VST are compatible with other current de-noising approaches in which the VST-based strategies are a recent research phenomenon for denouncing CT and X-Ray pictures, Poisson noise can be viewed as an additive Gaussian noise due to the use of VST. Researchers may therefore reuse the current Gaussian denoising methods, which accomplish many milestones, and creating a partial denoising method for handling Poisson noise is redundant.

V. IMPLEMENTATION OF RECONSTRUCTION ALGORITHMS

A computed tomography scan (CT or CAT) enables physicians to look within the body. To produce images of organs, bones, and other tissues, it uses a mixture of X-rays and a computer. It displays more particulars than a normal X-ray. A typical work of CT imaging starts with data acquisition and continues to data pre-processing to image reconstruction to segmentation and finally to analysis.

Data Acquisition

Originally, a sample is placed in the scanner field of view, and images of intensity are acquired for a set of projection angles. Ideally, any calculated image is an exact projection underneath the exact geometrical parameters of the scanned object. The data for the forecast is said to be accurate in that case. For parallel beam projection data, consistency conditions are specified. Unfortunately, there are a number of reasons why distinct projection images might be incompatible with each other.

- **Noise**

  The overall number of photons dispersed at the source of a given X-ray beam, I0, is Poisson. High signal-to-noise ratios (SNR) can therefore only be acquired if I0 is sufficient, and therefore the radiation dose is also sufficient.

- **Detector quality**

  Not all detector cells have the same sensitivity, and are likely to improve with the wear of detector plates.

  The projection data can also be standardized by calculating a dark field image, D (an image obtained when the X-ray source is turned off), and a bright field image B (an image obtained when the X-ray source is turned on but without the sample) to counter this issue:

$$I\ norm = I - D / B - D$$

- **Scattering**

  When an X-ray photon navigates an electron, there is a possibility that it will be dispersed, i.e. that it will continue on a refracted path with lower energy. A refracted photon like this is usually assumed not to reach the detector. Scattered photons could still be calculated however. This violates the assumption that each detector cell policies only non-attenuated X-ray photons. Each calculated value is instead a mixture of primary photons and dispersed photons. Note that the scattered ray's commitment is not inversely related to the primary rays participation. The calculated signal SNR then reduces successfully if the high modulating artifacts are on the primary ray line.

- **Photon starvation**

  As an X-ray beam passes through an object, the actual number of photons within that beam reduces. If the object comprises a very dense material, such as a metal, and if the X-ray beam's energy is not sufficiently high, then the whole X-ray beam may be dimmed. Information about the attenuation before and after the dense products are lost, resulting in artifacts or metal artifacts being stretched.

- **Misalignment**

  Projection data is often inaccurate if the geometric specifications of a given projection (i.e., source location and origin detector array (0;0)) are not what is believed to be. This can happen if the gantry that mounts the source and detector on is not balanced during its rotation.

- **Motion**

  In the whole acquisition process, the scanned sample is believed not to shift or change shape. But this is not feasible for other procedures, such as cardiac imaging. Advanced medical CT scanners have a very high speed of rotation, to eliminate this effect.

VI. DATA PRE-PROCESSING

Upon acquisition of the projection data, a pre-processing step is applied to start preparing the data for use in a reconstruction algorithm. This step involves the logarithmic transformation measurement, which converts the projection image intensity values into log-corrected attenuation quantities. Certain specific operations include rebounding (transforming data to another projection geometry) and adjusting data for one or more anomalies identified during the preceding process (e.g., seeking to correct projection errors). The data being pre-processed also includes the following issues.

- **Data Inconsistency**

  Any data inconsistency of the projection images acquired for which no corrections were made.

- **Partial Volume Effect**

  A partial volume effect (PVE) on data from the projection. Each detector cell has a certain diameter, and usually the edges of artifacts are not aligned with a detector edge.

- **Beam hardening**

  The calculated intensity value for polychromatic X-ray sources does not rely exclusively on the object's ray duration, but also on the X-ray beam's energy spectrum. The photons with low energy are usually consumed more strongly than photons with high energy, the shape of the energy spectrum can change as the beam moves through an object. This eliminates the linear relationship between both the radius length and the attenuation, culminating in inconsistent log-corrected projection data culminating in objects of reconstruction cupping and streaking, as can be known.

VII. RECONSTRUCTION

The reconstruction is carried out in the next process. For the proposed research, four reconstruction techniques are regarded. The reconstructed images frequently contain pixels whose values don't correspond to the original object's attenuation factors. They are related to errors in reconstruction or artifacts in reconstruction and may occur for a number of reasons.

- Any data inconsistency of the pre-processed data that was not corrected for.
- The partial volume effect (PVE) of the reconstruction grid.

Various types of incomplete data can be noted.

- A small number of projection directions,
- A limited angular range.
- Truncated projections.

This type of incomplete data impedes precise image reconstruction outside of the Field of View (FOV). Moreover, because typical reconstruction strategies are non-local (i.e., it is not possible to reconstruct precisely only a subset of the reconstruction domain), it is also not practical to reconstruct adequately within the FOV.

Suggested solutions to this problem involve completing projection data by extrapolating with a certain smoothing function or combining several scans with a moved sample or a lower dose of radiation on a complete detector array.

VIII. CONCLUSION

In this study, analytical and iterative reconstruction techniques has been studied to develop robust reconstruction algorithm. In Analytical reconstruction technique, filtered back projection algorithm have been explored where it applies interpolation techniques for reconstructing image, this technique inherently suffers under extreme noise levels, research show that it can be improved by adjusting the sparsity of polar roaster. The study further explores on iterative reconstruction techniques which is efficient from performance per se but with heavy trade off on computational time. Parallelization and image reconstruction techniques greatly improves the computation time. Several denoising techniques has been studied, total variation yields more interest due to its efficiency.

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