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A Novel Approach for Reduction of Radiation Dose in X – Ray Computed Tomography

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Abstract - Medical imaging has grown by leaps and bounds, although it is still emerging as a full grown arena of invention and research. Tomography is a technique for displaying a representation of a cross section through a human body or other solid object using X- Rays or ultrasound. Current imaging problems deal with understanding the trade-off between data size, the quality of the image and the computational tool used to create the image. The radiation dose reduction is done by reducing the x-ray tube current and exposure time (mAs) in repeated CT scans, a prior-image induced nonlocal (PINL) regularization is proposed for statistical iterative reconstruction via the Penalized Weighted Least-Squares (PWLS) criteria which is referred to as "PWLS-PINL". Specifically, the PINL regularization utilizes the redundant information in the prior image and the weighted least-squares term considers a data dependent variance estimation, aiming to improve current low dose image quality.

Keywords – CT, PWLS - PINL, statistical iterative reconstruction

I. INTRODUCTION

Computed Tomography (CT) is a widely used medical imaging method which is employed to visualize interior organs within the human body and obtain information of their structural properties from a set of X-ray projections. Starting with its introduction in the 1970s, CT has become an essential tool in medical diagnostic and preventive medicine and its use has increased very rapidly over the last two decades due to technological advances which have made the procedure much more user-friendly to both patients and radiologists. Tomographic imaging creates three-dimensional images of object properties by processing multiple measurements from transmitted or emitted energy.

II. LITERATURE SURVEY

Hua Zhang, *et.al* [1], proposed an idea of realizing radiation dose reduction by reducing the X–Ray tube current and exposure time (mAs) in repeated CT scans by proposing a prior image induced nonlocal regularization for statistical iterative reconstruction via the penalized weighted least squares criteria.T. Schubert, *et.al* [2], have discussed about a sacral, transneuroforaminal approach of obtaining a biopsy sample of a presacral lesion to minimize the risk of complications applied to a computed tomography based navigation system.Q. Xu, *et.al* [3], developed a dictionary learning based approach for low-dose X-ray CT and discussed about the sparse constraint in terms of a redundant dictionary is incorporated into an objective function in an iterative reconstruction framework and the dictionary can be predetermined before an image reconstruction task or adaptively defined during the reconstruction process.

Anando Sen, *et. al* [4], have proposed an idea of Region Of Interest (ROI) image reconstruction where the overall radiation exposure is reduced. It helps to reconstruct a specified region rather than the whole object is required.G.H Chen, *et.al* [5], has discussed a data acquisition scheme and an image reconstruction method is proposed to achieve time-resolved cardiac cone-beam computed tomography imaging with isotropic spatial resolution and high temporal resolution using a slowly rotating C-arm system. The enabling image reconstruction method is the Prior Image Constrained Compressed Sensing (PICCS) algorithm. The prior image is reconstructed from data acquired over all cardiac phases. Each cardiac phase is then reconstructed from the retrospectively gated data using the PICCS algorithm. L. Ouyang, *et.al* [6], proposed an idea of quantitatively evaluating the impact of the penalties on the performance of a statistics-based Penalized Weighted Least-Squares (PWLS) iterative reconstruction algorithm for improving the image quality of low-dose Cone – Beam CT (CBCT). J. H. Siewerdsen, *et.al* [7], discussed the development of large-area Flat-Panel X-Ray Detectors (FPDs) has spurred investigation in a spectrum of advanced medical imaging applications, including tomosynthesis and Cone-Beam CT (CBCT). L. Yu, *et.al* [8] discussed about iterative ML reconstruction which is limited to a Region Of Interest (ROI) without losing the advantages of a ML reconstruction. Rolf Clackdoyle and Michel Defrise [9], in their article they have considered only about the analytic methods.(2-D) reconstruction problem refers to a density function in two dimensions with measurement lines lying in the plane, and the three-dimensional (3-D) problem considers 3-D density functions and lines with arbitrary orientations in space. L. Yu, *et.al* [10], had summarized the general technical strategies that are commonly used for radiation dose management in CT.B. Zhao, *et.al* [11], discussed about evaluating the variability of tumor one-dimensional, bi-dimensional, and volumetric measurements on same-day repeated Computed Tomographic (CT) scans in patients with non–small cell lung cancer. Robert Azencott, *et.al* [12], proposed an idea about a novel method for image reconstruction in 3D tomography, called Searchlight Computed Tomography, which reduces the overall radiation exposure when primarily the reconstruction of a specified region of interest is required.

III. PENALIZED WEIGHTED LEAST SQUARE ALGORITHM

A. PWLS Criteria for CT Image Reconstruction

Mathematically, the X-ray CT measurement can be approximately expressed as a discrete linear system:

$$y = H\mu \qquad (1)$$

where μ denotes the vector of attenuation coefficients, i.e., $\mu = (\mu_1, \mu_2, \dots, \mu_N)'$ and y represents the obtained sinogram data (projections after system calibration and logarithm transformation), i.e.,$y = (y_1, y_2, \dots, y_M)'$, where "′" denotes the matrix transpose The goal of CT image reconstruction is to estimate the attenuation coefficients μ from the measurement y. According to the measurement model and the MAP estimation criterion, the mathematical formula for PWLS image reconstruction with a regularization term $R(\mu)$ can be expressed as:

$$\mu^* = argmin\{(y - H\mu)' \textstyle\sum^{-1}(y - H\mu) + \beta R(\mu) \qquad (2)$$

where $\sum$ is a diagonal matrix with the ith element of σ_i^2 which is the variance of sinogram data y. β is a hype-parameter that controls the strength of regularization.To determine the parameter σ_i^2 in eq. (3.3), can be used in several methods. Here, the variance of σ_i^2 is determined by the mean-variance relationship proposed is written as:

$$\sigma_i^2 = \frac{1}{,}\exp(\bar{p}_i)\,((1 + \frac{1}{,}\exp(\bar{p}_i)\,(\sigma_e^2 - 1.25)) \qquad (3)$$

where I_0 denotes the incident x-ray intensity, $\bar{p}_i$ is the mean of sinogram data y at bin i and σ_e^2 is the background electronic noise variance.

B. Overview of the PINL regularization

Traditionally, $R(\mu)$ in eq. (4) is designed by a simple weighted sum of the potential function on the different values of the neighboring pixels in the image domain , and can be described as

$$R(\mu) = \sum R(\mu_i) = \sum\sum w(k,j)\varphi(\mu_i - \mu_k) \qquad (4)$$

where index j runs over all image elements in the image domain. S_j represents the local neighborhood of the jth image pixel in two dimensions and $\boldsymbol{\varphi}$ denotes a convex and positive potential function satisfying $\boldsymbol{\varphi}(0) = 0$.

C. Implementation of the PWLS-PINL Method

In the implementation of the present PWLS-PINL method, the current CT images and the initial high-dose CT images are first reconstructed by the FBP method, and then a B- spline based image registration technique is adopted to generate the registered prior image from the initial high- dose CT image. For simplicity, this implementation is called as the PWLS-PINL algorithm

D. Data Acquisition

Anthropomorphic Torso Phantom: The image is scanned by a clinical CT scanner (Siemens SOMATOM Sensation 16 CT) at three exposure levels, *i.e.*, 17, 40, 100 mAs.

Numerical XCAT Phantom: To evaluate the influence of mismatch between the prior and current images on the performance of the PWLS-PINL and PICCS methods, the XCAT image is used to simulate the normal-dose and low-dose CT image volumes with the same anatomical structures.

Patient Data: The patient data is obtained with a patient consent for a chest CT study for medical reasons. The experimental data is acquired by the Siemens SOMATOM Sensation 16 CT scanner.

III. RESULTS AND DISCUSSIONS

Image reconstruction has a fundamental impact on image quality and therefore on radiation dose. For a given radiation dose it is desirable to reconstruct images with the lowest possible noise without sacrificing image accuracy and spatial resolution. Reconstructions that improve image quality can be translated into a reduction of radiation dose because images of acceptable quality can be reconstructed at lower dose.

A. SIMULATION PARAMETERS

The simulation parameters that are considered in this project are listed as shown in the Table 4.1 below

Table 1 Simulation parameters

No. of iterations	50,100,150,200,250
Type of image	JPEG image
Parameters to be analyzed	Peak Signal to noise ratio, Mean Square Error

B. SIMULATION RESULTS AND CONCLUSION

A three dimensional transverse CT scan of chest image data is taken as input. Initially the parameters for x-ray tube and detector in an x-ray source has been set. Then the direction of gantry has been set and filter is chosen. The CT scan of the image is obtained but the image appears blurred. In order to overcome it, the CT image is trained with Penalized Weighted Least Squares algorithm. It takes more number of iteration to reconstruct the transverse CT image. With less amount of image details the image is reconstructed.

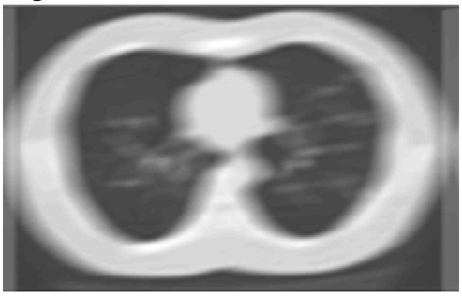

Fig. 1 Transverse CT scan of chest

Detector setting is done based on the varian Trilogy OBI (On Board Imager). The varian trilogy OBI provides high resolution and low dose digital imaging.

Fig. 2 Image obtained from PWLS –PINL algorithm

The image which is obtained from PWLS - PINL algorithm is trained on the basis of variation in the parameters such as computation time, noise and image quality. To obtain a region of interest (ROI) image more number of iterations is carried out.

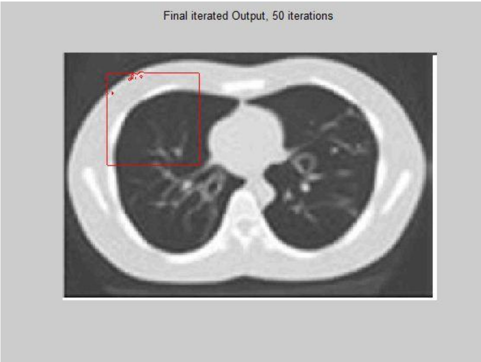

Fig .3 (a) Iteration 50

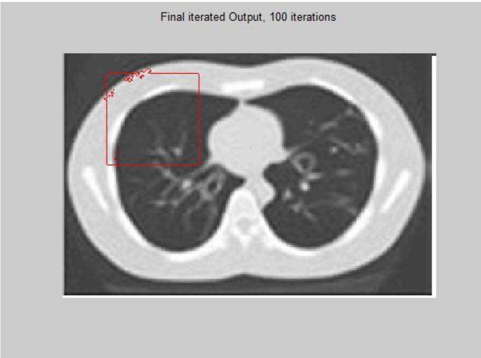

Fig .3 (b) Iteration 100

By increasing the iteration number the region inside the transverse CT image becomes visible. With less quantum of x-rays the image is reconstructed.

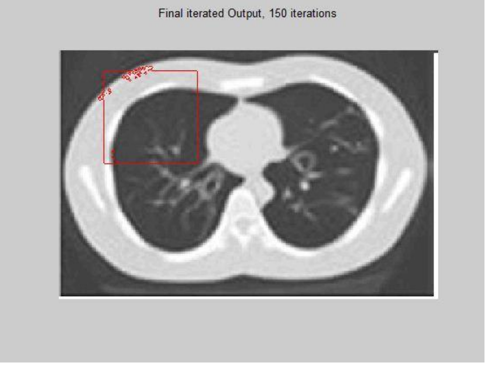

Fig .3 (c) Iteration 150

The image quality gets increased in the consecutive iterations. High level of radiation exposure leads to associated health risks in the form of radiation-induced carcinogenesis.

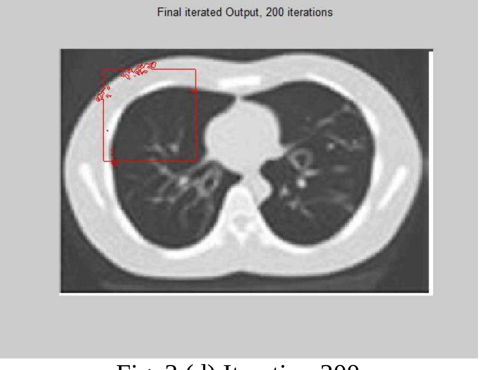

Fig .3 (d) Iteration 200

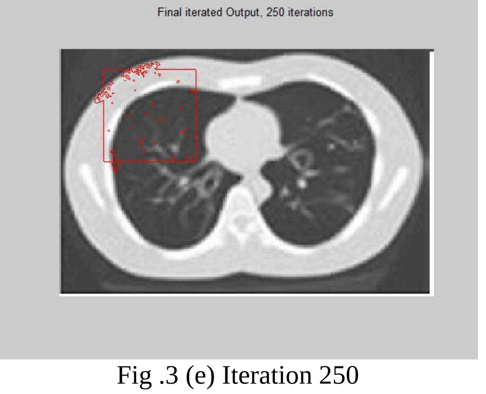

Fig .3 (e) Iteration 250

The parameters which has been set initially at the X-ray tube and detector in x-ray source provides less amount of radiation exposure to the patients. So, small number projections are taken. This gives an image which consists of less amount of image details.

The comparison graph for Peak Signal-to-Noise Ratio (PSNR) is given in Fig.4

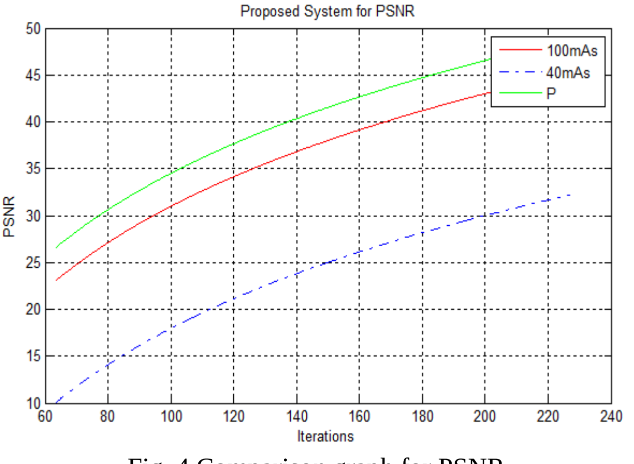

Fig. 4 Comparison graph for PSNR

Fig.5 shows that the proposed algorithm gives a low mean square error. The comparison graph for Mean Square Error is given in Fig.5

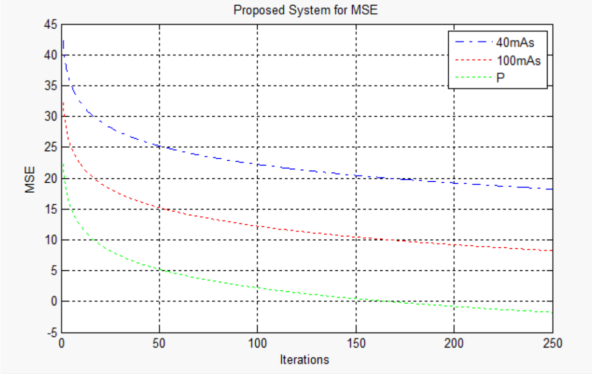

Fig .5 Comparison graph for MSE

Figure 6 shows the Penalized Weighted Least Squares Algorithm (proposed algorithm) gives a better image quality than the existing algorithm.

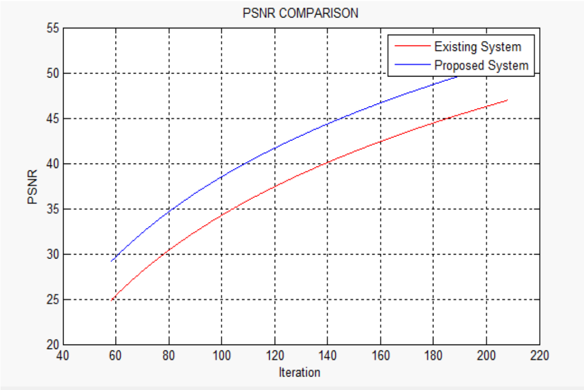

Fig. 6 PSNR comparison graph between proposed and existing system

The MSE value of the proposed system is compared with the existing system in order to find the better performance in reducing the MSE value and the Fig.7 shows the Penalized Weighted Least Squares Algorithm (proposed algorithm) gives a low mean square error value than the existing algorithm.

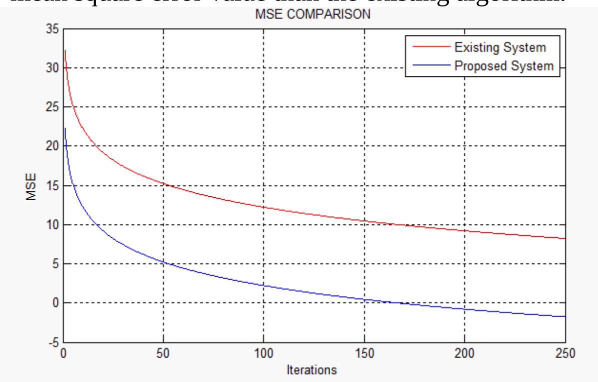

Fig .7 MSE comparison graph between proposed and existing system

C. SIMULATION PARAMETERS

The peak signal-to-noise ratio and mean square error of the image is given below.

Table 2 Simulation parameters

Simulation Parameters	**Normal Radiation**	**Low Radiation**	**PWLS – PINL**
PSNR	24.50 dB	9.85 dB	26.34 dB
MSE	33	42	21

This image takes nearly 250 iterations to reconstruct. By using Penalized Weighted Least Squares algorithm via a Prior image Induced Nonlocal Regularization the tomographic image is reconstructed. By training the CT image, the region of interest image is reconstructed.

IV. CONCLUSION

Computed Tomography involves exposure of the patient to X-Ray radiation, with associated health risks (in the form of radiation-induced carcinogenesis) essentially proportional to the levels of radiation exposure. ROI tomography is motivated by the goal to reduce the overall radiation exposure when primarily the reconstruction of a specified region rather than the whole object is required. The problem of reconstructing images at the boundary of a domain belong to the class of inverse problems. Early tomographic image is reconstructed using back projection algorithm. In this paper, PWLS - PINL algorithm is used. By setting the parameters of x-ray tube and detector in x-ray source and the direction of gantry, the radiation exposure is reduced. The image thus obtained contains less number of image data. More number of iterations are required to reconstruct the image. With this limited amount of image details, the transverse CT image is reconstructed.

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