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Efficient Lung Computed Tomographic Images Reconstruction

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Abstract

To obtain a sufficient visible medical image from a computed tomographic-scan exam, it is necessary to pass through a reconstruction step. Therefore, the quality of the obtained image depends essentially on the efficiency of the applied reconstruction method. In this work, we propose a new method of reconstruction applied and tested on lung images based on the combination of two well-known basics tomographic reconstruction algorithms: Filtered Back Projection (FBP)and Ordered-Subsets Expectation Maximization (OSEM). The combination of these two algorithms is followed by a post-processing stage offering better quality image ensured by Gaussian filtering. The use of these two basics algorithms in this hybridization is justified by an evaluation analysis which ensure the best quality parameters for the relative norm error of the simulated projection (dp),the normalized absolute error (NAE), the normalized cross correlation (NCC), the relative norm error of the reconstructed image (df), the mean square error (MSE), the structural content (SC)and the peak signal to noise ratio (PSNR) of the proposed method compared to other literature algorithms. In addition, and to confirm the significant difference of , the Dunnett "test t"' was executed on the means of the quality parameters. In fact, the Dunnett "test t" obtained a p- value ($\prec$ 0.05) for all the means of the quality parameters which attest the superiority of the proposed method.

Keywords: Computed tomography (CT); Filtered Back Projection (FBP); Gaussian filter; Ordered-Subsets Expectation Maximization (OSEM); Tomographic reconstruction.

1. Introduction

Computed tomography (CT) is a cross-sectional imaging technique (1). It uses the attenuation of X-rays by body organs to create projections. By sending X-rays from different angles around the object, a collection of projections (shadow pictures) will be created.

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Combining these pictures (projections) results in a sinogram, which represents the image of a body cross-section (2), (3). Reconstruction techniques are then used to create images. Applying a good reconstruction technique affects well the quality of the resulting image. The commonly used tomography reconstruction method is the filtered back projection (FBP). Otherwise, there exist many other techniques that can be classified into two families: iterative methods and analytical methods .Filtered back projection (FBP)and Back Projection (BP) belong to the first family of reconstruction techniques. While Maximum Likelihood Expectation Maximization (MLEM),Ordered-Subsets Expectation Maximization (OSEM),Algebraic Reconstruction Technique (ART) and Simultaneous Algebraic Reconstruction Technique (SART) belong to the iterative methods. Many studies have shown that iterative reconstruction algorithm is better in lung CT images reconstruction, permitting radiation exposure reduction without distorting the image quality. In fact,Pontana et al. (4) showed that IR using three iterations provides similar image quality to that of conventional FBP reconstruction, but with a 35 % reduction in radiation. Kligerman et al. (5) showed that the use of "IR techniques can improve image quality and reduce image noise of CTPA". Willemink et al. (6) showed that Iterative Reconstruction (IR), compared to FBP at the same radiation dose, improves objective and subjective image quality and reduces artifacts and noise. Pontana et al. (7) showed that reconstruction with Sinogram Affirmed Iterative Reconstruction (SAFIRE) provided good image quality and diagnosis value comparable to those with full-dose FBP. Montet et al. (8) showed that CT Pulmonary Angiography (CTPA) using low milliampere (mA) setting reconstructed with Model-Based Iterative Reconstruction (MBIR) is equivalent to routine Computed Tomographic Pulmonary Angiography (CTPA) reconstructed with FBP. Chen et al.(9) proposed an algorithm, called line integral alternating minimization (LIAM), for dual-energy X-ray CT image reconstruction. LIAM allows for a tunable discrepancy between the basis material projections and the basis sinograms. A parameter is introduced that controls the size of this discrepancy, and with this parameter the new algorithm can continuously go from a two-step approach to the joint estimation approach. LIAM alternates between iteratively updating the line integrals of the component images and reconstruction of the component images using an image iterative deblurring algorithm. An edge-preserving penalty function can be incorporated in the iterative deblurring step to decrease the roughness in component images. The iterative algorithms have as inconvenient the choice of the estimated image and therefore the slow convergence. Tiwari et al. (10) proposed an hybrid method composed in the primary part by the SART that is applied to overcome the problems of initialization and slow convergence . "The task of primary part is to provide an enhanced image to secondary part to be used as an initial estimate for reconstruction process. The secondary part is composed by the OSEM algorithm and the anisotropic diffusion (AD) that is used prior to deal with poor posedness, but this model uses two iterative algorithms known both by their slow convergence". A comparative analysis of this method with some other standard methods in the literature (MLEM, OSEM, MLEM+AD) is presented both quantitatively and qualitatively for a standard medical image and phantom test data . "Tiwari's method yields significant improvements in reconstruction quality from the projection data". In this paper, we present a new method for solving these problems. The proposed method is a

hybrid model combining OSEM iterative algorithm, known to be a technique giving better quality image than other iterative techniques such as ART, SART and MLEM, to FBP analytical algorithm, characterized by its fast convergence, as an initial guess. The new method is applied to many lung CT images and compared with other algorithms presented in the literature review. The paper is organized as follow: Section 2 is divided into two parts. The first one describes basic principles of tomographic reconstruction while, the second part presents the proposed method. Section 3 present the simulation results of lung CT images reconstruction by presenting a comparative study between the proposed method and other literature methods. This study is based on many criteria such as mean square error (MSE), relative norm error of the reconstructed image (df), normalized cross correlation (NCC),relative norm error of the simulated projection (dp), structural content (SC), Normalized absolute error (NAE)and peak signal to noise ratio (PSNR) . Finally, we presents the obtained results on the conclusion.

2. Methods

2.1. Principle of tomography reconstruction

Basically, tomography imaging is based on reconstructing an image from its projections. Each projection is an integral line of some parameters of the object. We represent an object noted by f(x,y) and its projection noted by P_ϕ in figure 1.

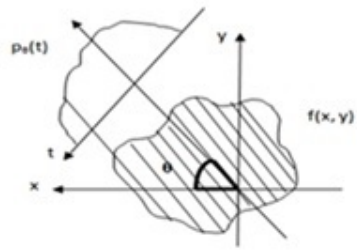


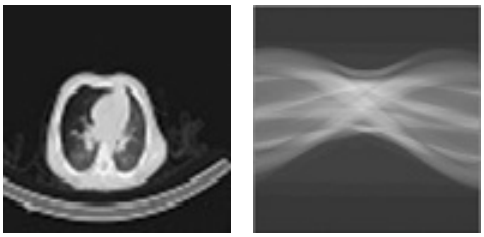
Figure 1: An object f(x, y) and its projections,$p_\phi(t)$ are shown for an angle ϕ.

The projection (11), as shown in figure 1, is obtained by compiling the 2D radon transform (RT) of the distribution f(x,y), using the following equation 1 :

$$p_\phi(t) = \int\int f(x,y).\delta(c.\cos(\phi + y.\sin\Phi - t)dx.dy \tag{1}$$

where f(x,y) represents the 2D image to be reconstructed, δ is the Dirac delta function, and $P_\phi$is often referred to as a sinogram. A sinogram is a 2D image in which, the vertical axis corresponds to the angular position of the detector and the horizontal axis represents the count location on the detector A typical slice image and its RT are shown in figure 2.

The reconstruction algorithms make it possible, from the set of projection measurements $\{p_\phi(t), \phi \in [0, \Pi[, t \in R\}$(with $p_\phi(t) = (-t, \phi, +\pi)$), to find values of the object function f



(a) (b)

Figure 2: (a)Lung CT image, (b)Corresponding sinogram (coverage angle ranging from 0 to 180 and rotational increment of 1).

at any point of the space $\{f(x,y),(x,y) \in R^2\}$. For this reason, it is necessary to reverse the operator of Radon (12). There are various reconstruction methods that can be classified in two families: analytical and iterative algorithms. A literature review presenting different reconstruction algorithms, their applications, their advantages and their drawbacks is resumed in the tables 1 and 2.

Table 1: Description of analytic reconstruction.

Description	Analytic reconstruction
Principle	-A continuous-continuous modeling. -It allows finding the inverse operator of Radon in an analytical way using the Fourier Slice theorem. -The central slice theorem makes it possible to reconstruct a tomographic section directly by means of the Inverse Fourier Transform.
Advantages	-Very fast in time computing. -High quality reconstruction. - Direct inversion.
Drawbacks	-Very sensitive to noise. -Cannot provide acceptable reconstructions in the case of a small number of projections or that of projections acquired over a reduced angular domain.
References	Natterer et al. (13), Kak et al. (14), Chetih et al.(15), Buzug et al. (17), Currie et al. (18),Peyrin et al. (19).

2.2. Proposed method

Iterative algorithms generally give a good image quality but they converge slowly. The used initial guess (estimate image) is essentially on the cause of this slow convergence. We propose in this paper a method with accelerated convergence while conserving a good quality image.

The proposed hybrid method is based on an accelerated version of the statistical MLEM algorithm OSEM (1 iteration/45 subsets). A FBP based image reconstruction is used as an initialization for OSEM and finally a Gaussian filter parameter sigma (σ) less than 1 is applied. The proposed method is composed of two stages: the combined reconstruction

Table 2: Description of iterative reconstruction.

Description	Iterative reconstruction
Principle	-A discrete-discrete modeling. -It allows to finding a solution by successive estimates. -The procedure is initiated by arbitrarily creating a first estimate. - for algebraic algorithm, estimate image is a uniform black image and the correction is c the form of an addition . -For statistical algorithm, estimate image is a uniform white image and the correction is the form of a multiplication .
Advantages	-Robustness. -Possibility of integrating information a priori on the image. -They allow reconstruction of volume from incomplete data (Need limited number of views or restricted angular range).
Drawbacks	-Slower in time computing.
References	Tiwari et al. (10), Bruyant et al. (11), Chetih et al. (15), Shepp et al. (16), Tsui et al. (20), Fessler et al. (21), Lee et al. (22), Matthies et al. (23), Hadson et al. (24), Ramirez et al. (25), Scherl et al. (26), Leong et al. (27), Xu et al. (28), Andersen et al. (29).

stage and the post-processing stage as presented by figure 3. The principle of the proposed method is to find a solution through successive estimates. Measured projections are compared with those corresponding to the current estimate.
The result of the comparison is used to modify the current estimate, thereby creating a new estimate. The procedure is initiated by the FBP based image reconstruction, creating the first estimate.

2.2.1. First stage: combined reconstruction

OSEM is widely used by modern CT scanner (30),(28). It was proposed to accelerate the reconstruction process using the MLEM method (25), (26).
Since its onset to the domain of image reconstruction by Shepp and Vardi (16)in 1982, the MLEM method remains the basis of the most popular statistical method of reconstruction and has provided the basis of other various algorithms (22). The MLEM obtained image is computed using equation 3.

$$f_i^{n+1} = f_i^n \frac{1}{\sum_i R_{ij}} \sum_j R_{ij} \frac{P_j}{\sum_i R_{ij} f_i^n} \tag{2}$$

Where P_j is the measured projection data at bin j,f^{n+1} is the estimate of image pixel i after the nth iteration, R_{ij} is the transfer matrix from image pixel i to projection bin j,

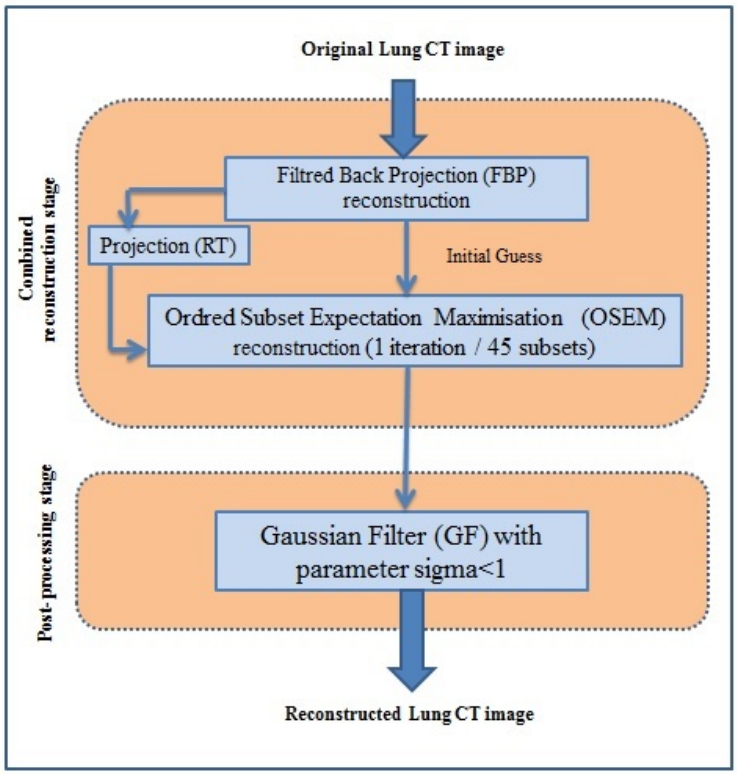


Figure 3: Different steps of the proposed algorithm.

$\sum_i R_{ij} f_i^n$ is the retroprojection of the estimate image f_i^n and $\sum_i R_{ij}$ is the back projection of the projection array p. Indeed, the similarity between measured and estimated sinograms is assessed using a likelihood that is statistical parameter . The algorithm is designed to maximize it (by the process called the expectation maximization), while taking account that the measured data is tainted by a noisy Poisson (25). This last point confers at this algorithm to be well adapted for the reconstruction of the transmit regions of little photon. The pixels of the cutting that will start the process contain positive and identical value (usually 1).

With OSEM algorithm, the set of projections is divided into blocks (or subsets). A large blocks size would be used to speed up the reconstruction (28). The MLEM is then applied on each block in turn, as a sub-iteration. The first full iteration is complete when all blocks were processed (10). This algorithm provides many advantages including and the ability to reduce noise in low radiation dose (29)and better image quality for noisy data (12) .

But the OSEM method, like any iterative algorithm, has the drawback of how to choose the initial guess. Usually, this later is chosen arbitrarily (often 1) and it converges slowly. To overcome the problems of initialization and slow convergence , we use the analytical algorithm FBP as an initial guess. It must be noted that FBP has good performances as an analytical reconstruction algorithm (31). The FBP algorithm is the reconstruction by back projection of filtered projections (17). This is mathematically expressed as in equation 4:

$$f(x,y) = \int_{-\infty}^{+\infty} (\int_{-\infty}^{+\infty} |\nu| p(s,\phi) e^{2i\pi\nu s} d\nu) d\phi s = xcos\phi + sin\phi \tag{3}$$

where f(x, y) is the image to be reconstructed, $p(s,\phi)$ is the projection and $|\nu|$ is a ramp filtering. therefore, modified OSEM = OSEM (initial guess image f(0) given by FBP) is presented in equation 4 (initial value: $f_j^0 = f_{FBP}$):

$$f_j^{n+1} = f_j^n . \frac{\sum_{pi \in p_{set}} \frac{p_i}{f_{pi}} . w_{ij}}{SOW_j} \tag{4}$$

Where p_i is the measured projection,f_{pi} is the pixel value calculated from forwarded projection,w_{ij} is the transfer matrix, f_j^{n+1} is the estimate of image after the nth iteration, SOW_j is the sum of columns and f_j^n is the calculated projection at the nth iteration. The main steps of the combined reconstruction are described in figure 4.

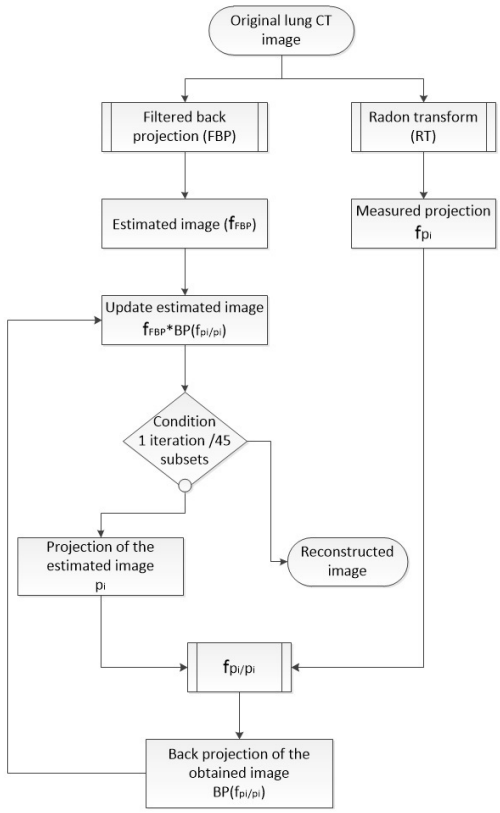


Figure 4: Different steps of the combined reconstruction stage

2.2.2. Second stage: post-processing

The obtained image at this stage is very blurry. To enhance the image quality, it is necessary to use a filter in order to eliminate the blur. The Gaussian filter is a special filter with isotropic properties. It is applied by convolution and it uses a mask (matrix), applied on each pixel (32),(33). The Gaussian filter is described by the function G (x, y):

$$G(x,y) = \frac{1}{2\pi\sigma^2}.e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{5}$$

Where y and x are the number of columns and rows respectively. The sigma parameter is called the standard deviation, and determines the width of the Gaussian cloche. Generally, Gaussian filters with a sigma < 1 are used to reducing efficient in blur.

3. Results and discussion

The comparative analysis of the proposed method is presented with conventional iterative and analytic reconstruction methods such as BP, FBP, ART, MLEM, OSEM, SART and also non-conventional techniques like Tiwari method. For quantitative analysis, various performance measures are used. The description of these parameters is defined as follow:

- df (The relative norm error of the resulting images) is used and defined as

$$df = \frac{\|f - f'\|^2}{\|f\|^2} \tag{6}$$

  Where f' is the reconstructed image and f is the original image.

- dp (The relative norm error of the simulated projection) is defined as

$$dp = \frac{\|p - p'\|^2}{\|p\|^2} \tag{7}$$

  Where p' is the simulated projection and p is the measured projection.

- MSE (Mean square error) is defined as

$$MSE = \frac{1}{N}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[f_{j,k} - f'_{j,k}\right]^2 \tag{8}$$

  Where M and N are the dimensions of the images, f' is the reconstructed image and f is the original image .

- NCC(Normalized cross-correlation) is one of the methods used for template matching, a process used for finding incidences of a pattern or object within an image. It is defined as:

$$NCC = \sum_{j=1}^{M}\sum_{k=1}^{N}\left(f_{j,k} - f'_{j,k}\right)^2 / \sum_{j=1}^{M}\sum_{k=1}^{N} f'^2_{j,k} \tag{9}$$

- SC (Structural content) is the measure of image similarity based on small regions of the images containing significant low level structural information and it is defined as

$$SC = \sum_{j=1}^{M}\sum_{k=1}^{N} f^2_{j,k} / \sum_{j=1}^{M}\sum_{k=1}^{N} f'^2_{j,k} \tag{10}$$

- PSNR (Peak Signal to Noise Ratio) is defined as:

$$PSNR = 10log\left(\frac{255}{\sqrt{MSE}}\right) \tag{11}$$

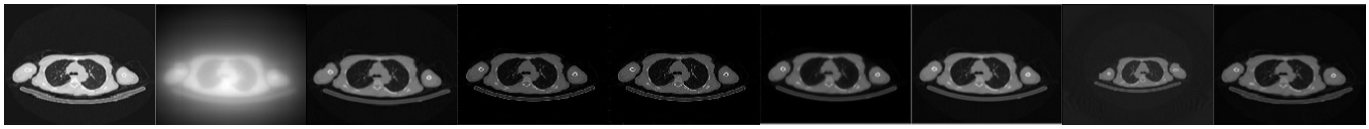
Smaller values of df, NCC dp and MSE indicate that the resulting reconstructed image has a better quality image. However, higher values of PSNR and SC indicate that the reconstructed image has a better quality image.

Two test are used: the first case is a modified shepp-logan phantom of size 64×64 and 120 projections angles was used. The simulated data was all Poisson distributed. The second test case for simulation was 120 thoracic CT exams(265 slices) acquired at the department of radiology in Salah Azaiez Institute. For both the test cases, we simulated the sinograms with total counts amount 6 × 105. A Poisson noise of magnitude 15 is added to projections. During the primary reconstruction of the proposed method, FBP was run to produce the initial estimate of the image to be used in secondary reconstruction step of the proposed algorithm. In secondary reconstruction the value of sigma used by the Gaussian filter was less than 1. The proposed algorithm was run for 1 iterations 45 subsets for simulation purposes. The visual results of the reconstructed images for both the test cases obtained from different algorithms was shwon in fig 5 and fig 6. The experiment reveals the fact that proposed hybrid method effectively eliminated Poisson noise and has better quality of reconstruction in term of dfs, dps, NCCs, MSEs, SCs and PSNRs. This figures also show that in the image reconstructed by the proposed method, the bronchi-ole and the parenchym are well drawn compared to the other methods. Table 3 and 4show quantification values of df, dp, NCC, MSE, SC and PSNR in for both the test cases, respectively. From this table, we can first deduct the efficiency of the OSEM algorithm compared to other iterative algorithms MLEM, ART and SART (30). ART and MLEM algorithms converge slowly to

the final reconstructed image. They require from 20 to 30 iterations to converge while SART algorithm converges in only one iteration. But also OSEM converges in a single iteration with the particularity of using 45 subsets. Values of df, dp, NCC and MSE obtained with OSEM are less than those obtained with MLEM, ART and SART algorithms. Higher values of SC and PSNR are obtained by OSEM algorithm. The results show that OSEM provides the best image quality. However, the OSEM algorithm takes less time to complete the process than MLEM, ART and SART.
Both the visual displays and the quantitatives results suggest that the proposed model is preferable to the existing reconstruction methods. From all the above observations, it may be concluded that the proposed model is performing better in comparison to its other counterparts and provide a better reconstructed image. In the end,the proposed method has to help the practitioner by higher better highlighting object of interests or facilitating the automatic extraction of characteristic feature.

(a) original image. (b) BP (c) FBP. (d) MLEM. (e) ART. (f) OSEM. (g) SART. (h) Tiwari method. (i) proposed method.

Figure 5: The modified Shepp–Logan phantom with different reconstruction methods.



(a) original image. (b) BP (c) FBP. (d) MLEM. (e) ART. (f) OSEM. (g) SART. (h) Tiwari method. (i) proposed method.

Figure 6: The Lung CT image with different reconstruction methods.

In order to verify that there is a significant difference between the means of the image quality parameters of the proposed method and those of the other methods, we used the Dunnett test which is a post- Hoc Test (or the multiple comparison test) (34). Dunnett is a test for comparing one sample (method) to each of the others, but not for comparing the others. A p-value < 0.05 was considered statistically significant.

For the comparison of different means (df, dp,MSE,NCC,SC and PSNR), we apply the analysis of variance (ANOVA) in order to decide if all means are equal or mean which is different from others (35). If we get a significant result, we can conclude that globally there is a difference between group means. However, we must identify those with significant difference. We must so use post-hoc multiple comparison test (Dunnett test). The results of the tests are presented in table 5. From this table, we clearly observe that the value of p=0.000 for df, dp, MSE, NCC, SC and PSNR is less than 0.05 for all methods. So, we

Table 3: Different performance measures for the reconstructed images in Fig.5

Performance parameters	df	dp	MSE ($\times 10^9$)	NCC ($\times 10^4$)	SC ($\times 10^{-6}$)	PSNR
BP	242.052	0.248	4.018	4.136	3.657	0.0450
FBP	161.649	0.023	2.377	3.239	4.707	0.0586
ART (30 iter)	187.193	0.156	3.711	3.957	4.520	0.0469
MLEM (20 iter)	193.217	0.123	3.615	3.653	4.576	0.0475
SART (1 iter)	175.118	0.031	3.573	3.520	4.723	0.0478
OSEM (1 iter, 45 sub)	170.015	0.025	3.715	3.417	4.653	0.0468
Tiwari method	161.838	0.020	2.976	3.331	4.836	0.0523
Proposed method	143.271	0.012	2.351	2.816	5 .142	0.0589

Table 4: Different performance measures for the reconstructed images in Fig.6

Performance parameters	df	dp	MSE ($\times 10^7$)	NCC ($\times 10^3$)	SC ($\times 10^{-6}$)	PSNR
BP	276.53	0.316	5.639	7.305	3.478	0 .183
FBP	187.342	0.347	2.177	4.471	4.835	0.272
ART (30 iter)	197.911	0.107	3.562	3.820	4.400	0.193
MLEM (20 iter)	197.621	0.115	3.559	3.562	4.459	0.195
SART (1 iter)	179.380	0.108	3.795	3.485	4.381	0.192
OSEM (1 iter, 45 sub)	177.341	0.024	3.530	3.425	4.566	0.197
Tiwari method	163.686	0.014	2.940	3.339	4.725	0.203
Proposed method	135.324	0.005	2.432	2.631	5 .018	0.221

Table 5: Multiple comparisons: Dunnett "Test t"

Methods	p(df)	p (dp)	p(MSE)	p(NCC)	p(SC)	p(PSNR)
BP/Proposed method	0.043	0.000	0.000	0.003	0.000	0.032
FBP/Proposed method	0.000	0.021	0.004	0.001	0.030	0.000
ART/Proposed method	0.005	0.030	0.030	0.075	0.000	0.028
MLEM/Proposed method	0.002	0.000	0.020	0.000	0.000	0.000
SART/Proposed method	0.015	0.045	0.000	0.025	0.000	0.000
OSEM/Proposed method	0.015	0.045	0.000	0.025	0.000	0.000
Tiwari/Proposed method	0.022	0.001	0.009	0.000	0.000	0.032

can conclude that the difference of means of these quality parameters is significant. These results confirm the superiority of the proposed method.

4. Conclusion

In this work, a new hybrid algorithm of lung CT images reconstruction is proposed in order to resolve the problems of choosing the initial estimate and slow convergence . Obviously, the proposed method should be efficient in terms of accuracy and quality of

obtained results. In fact, to treat the problem of slow convergence and initialization in the classical OSEM, a FBP based image reconstruction is used as an initial guess. To prove the efficiency of OSEM algorithm, we compared it with other iterative algorithms (ART, MLEM and SART). The obtained results show that OSEM has a better quality-image than the other basics algorithms. We compared also our proposed method with different literature algorithms. The obtained reconstructions using our proposed method are qualitatively and quantitatively better. Indeed df, dp, MSE and NCC obtained with the proposed method are lower than those obtained with other algorithms. Contrariwise, SC and PSNR values obtained with our proposed algorithm are higher than those obtained with other algorithms. The means of the image quality parameters of the proposed method and the means of the image quality parameters of other methods are significantly different ($p < 0.05$). This proves the superiority of our proposed method in offering a better quality-image for lung CT reconstructed images.

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Figures

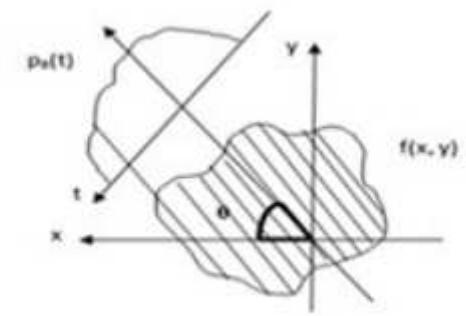


Figure 1

An object f(x, y) and its projections,pφ(t) are shown for an angle φ.

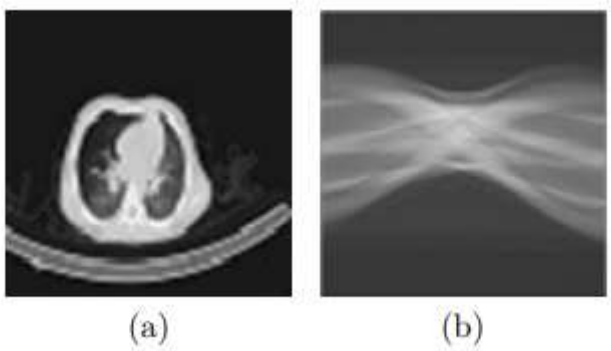


Figure 2

(a)Lung CT image, (b)Corresponding sinogram (coverage angle ranging from 0 to 180 and rotational increment of 1).

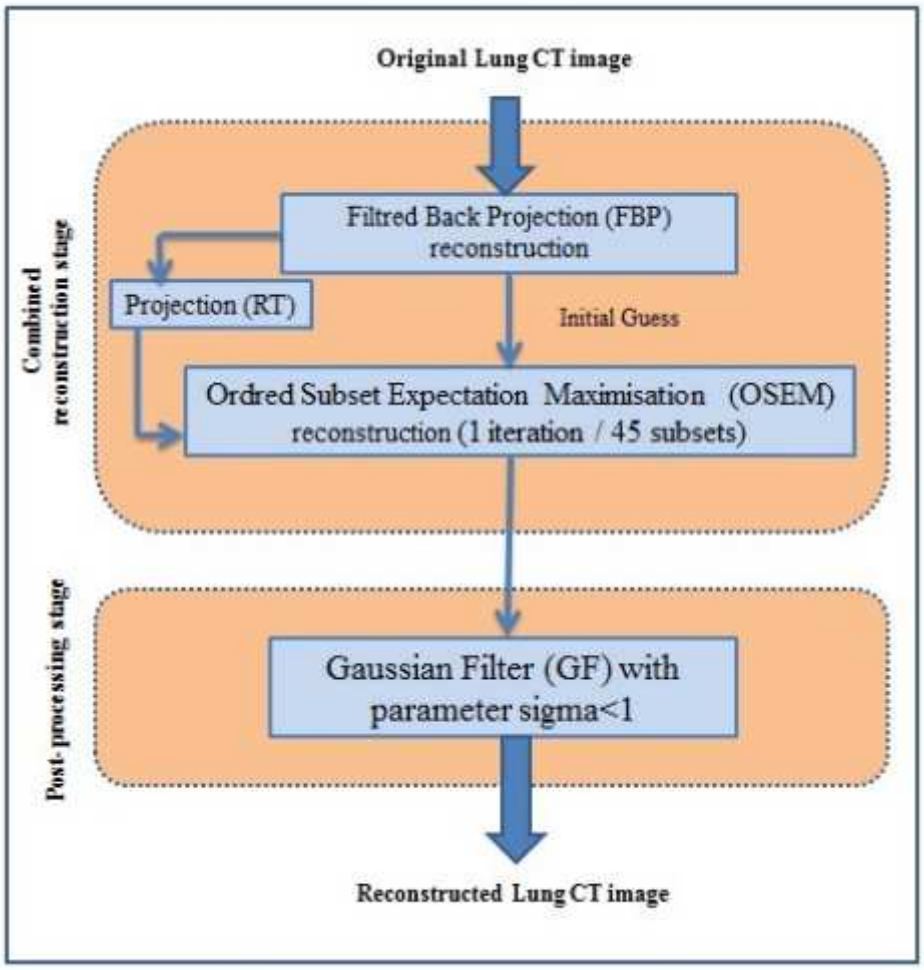


Figure 3

Different steps of the proposed algorithm.

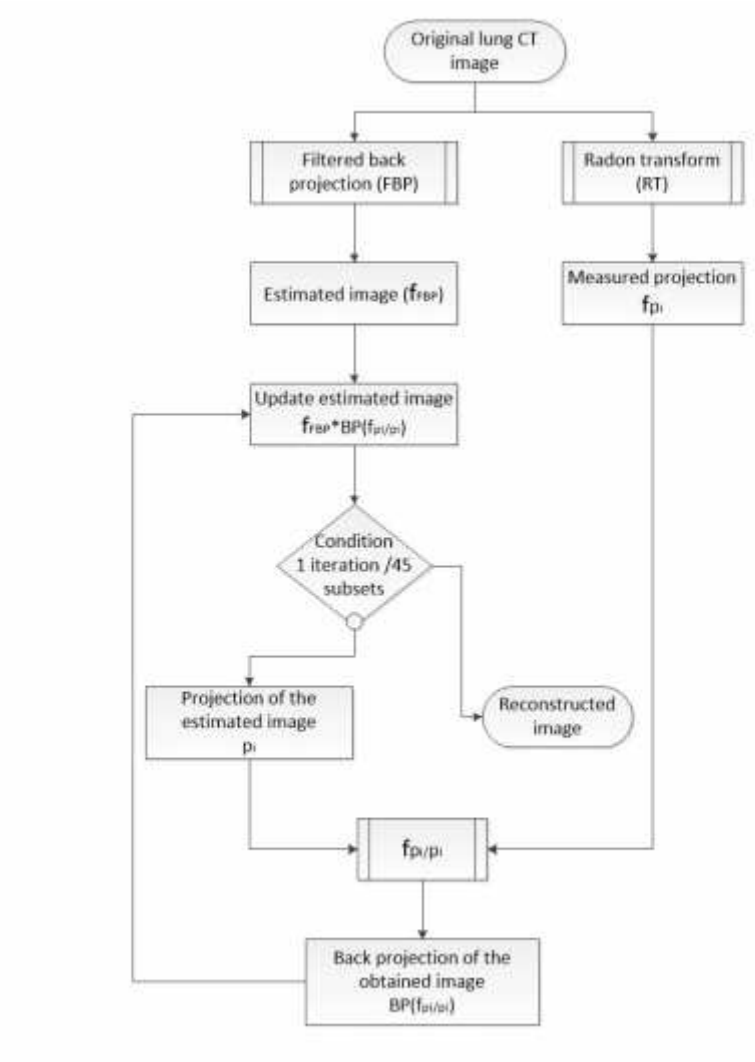


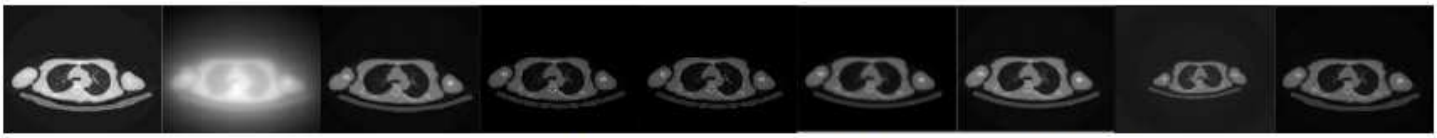
Figure 4

Different steps of the combined reconstruction stage

(a) original image. (b) BP (c) FBP. (d) MLEM. (e) ART. (f) OSEM. (g) SART. (h) Tiwari method. (i) proposed method.

Figure 5

The modified Shepp–Logan phantom with different reconstruction methods.



(a) original image. (b) BP (c) FBP. (d) MLEM. (e) ART. (f) OSEM. (g) SART. (h) Tiwari method. (i) proposed method.

Figure 6

The Lung CT image with different reconstruction methods.