An Expeditious Parallel Maximum Likelihood Expectation Maximization 3D Image Reconstruction Technique for CBCT

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Abstract

Computed Tomography signifies an imaging process that constructs cross sectional images, which reveal the internal structure of a scanned object in a nondestructive manner. Cone-beam CT is one of the most advanced developments in CT imaging, which presents an indispensable imaging technique that constructs three-dimensional images from the scanned object, Using cone-beam X-ray projections rather than the more often used fan-beam planar projections ensures quicker but safer three-dimensional imaging with less radiation than traditional CT imaging methodologies. However, these advancements come at the expense of a challenging 3D reconstruction issue that still requires changes in the speed and accuracy of the reconstructed image. In this article, we present a parallel implementation of an efficient parallel Maximum Likelihood Expectation Maximization (MLEM) algorithm for CBCT that provides a more reliable and faster reconstruction even with a small number of projections. We reconstructed a test volume image with this parallel version of the MLEM algorithm and used various image quality indices to test the effects of our proposed approach as well as the effect of the number of iterations on the reconstruction time and image quality. According to the data, the reconstruction of volume images using the proposed parallel algorithm was quicker than the standard reconstruction method using the non-parallel MLEM algorithm

I. INTRODUCTION.

CT (computed tomography) was first used in the early 1970s. It was previously known as computed axial tomography, or (CAT) scanning. The term computed was used in the summary to emphasize the computer's critical role in the advancement of this technology [1]. This medical imaging technique collects projection data from a scanning target and uses it to recreate cross-sectional images. The rotation of an X-ray source and a detector unit on opposite sides of each other produces the projection results. The three major types of X-ray beam are parallel, fan, and cone beam, indicating that CT image restoration techniques are dependent on the shape of the X-ray beam [2]. Fan-beam imaging produces two-dimensional (2D) images from its projection acquisition process. A projection at a given angle is the image's integration in the direction defined by that angle. A sinogram is a set of projections obtained from various angles during a CT scan that is used in the reconstruction process. Cone Beam Computed Tomography (CBCT) is a 3D expansion of 2D fan-beam CT tomography, obtaining a volume of projection data from a single rotation of the 2D detector array. As opposed to traditional CT, the CBCT technique has many benefits, including faster scan time, lower X-ray radiation exposure, and so on [3]. One of the primary benefits of CBCT is that it saves time during the data collection phase [4]. After collecting a volume of sinogram data, 3D image reconstruction techniques are used to recreate the volume image. The mathematical techniques used in the reconstruction process are classified as analytical, which use the concept of the central slice theorem, such as the Feldkamp, Davis, and Kress (FDK) method [5], and iterative, which attempt to solve the reconstruction problem by converting it into a system of simultaneous linear equations and then resolve to iterative methods, such as the ART and the MLEM algorithms [6,7]. The MLEM has recently gained popularity as a result of recent advances in computing power through evolved CPU, GPU, and parallel computing. Some previous studies explored 3D reconstruction techniques for CBCT, while others used non-parallel reconstruction approaches and others used parallel computation approaches to improve the reconstruction process's output speed. Kubra Cengiz and Mustafa Kamasak [8] used the Shepp-Logan test phantom to apply an iterative algorithm in the non-parallel reconstruction. The achieved reconstruction speed was poor, with a single iteration taking nearly (13) minutes for just (11) projections. Noor Hussein Fallooh [9] conducted extensive research on 3D image reconstruction algorithms in CBCT for both iterative and analytical approaches. The observed results were compared to varying numbers of iterations and image quality tests. In addition, Jorge Aviles [10] developed an iterative reconstruction approach with a limited number of predictions. Despite the fact that the projection data used was limited, the reconstruction time took more than three and a half hours. Jian Fu et al. illustrated the use of analytical and iterative algorithms [11]. Their restored pictures were of poor quality. This study found that iterative algorithms needed some specialized work to improve reconstruction speed. Parallel computing experiments, on the other hand, demonstrated significant gains in computation time. W. Qiu et al. demonstrated a substantially shortened reconstruction time for a single iteration using the ART algorithm in [12]. Z. Fan and Y. Xie used a GPU in [13], which resulted in a faster calculation time with the ART algorithm for just 60 projections, but they mentioned that their methodology did not yield high-quality images. Claudia de Molina et al. suggested a GPU-accelerated iterative reconstruction method for limited-data CBCT systems in [14]. Because of the use of the GPU, the authors introduced a time reduction, resulting in a complete reconstruction time reduction from many hours to a few minutes.

To the best of our knowledge, no studies on the statistical MLEM algorithm image reconstruction using parallel computation have been conducted. In this paper, we show a prompt parallel version of the MLEM algorithm for CBCT and compare its output to the non-parallel version of the MLEM algorithm. The image reconstruction outputs are measured over

a series of iterations in terms of reconstruction accuracy, speed, and X-ray radiation exposure quantity, which is affected proportionally by the number of projections. As opposed to the non-parallel technique, the findings suggest a substantial decrease in computation time. Furthermore, even with a small number of projections, our implementation offers improved picture consistency. The format of this paper is as follows: first, an outline of projections data generation is presented, followed by a detailed description of the MLEM reconstruction technique. The suggested parallel image reconstruction implementation is then seen.

Projection Data Initiation

Projections are an arrangement of rays that enter an object at some orientation angle during a CT scan. The main notion of a projection at a given angle is that it represents the integration of the image in the direction specified by that angle [7]. A two-dimensional projection $p(i,\theta)$ at the angle (θ) is represented by the following equation:

$$p(i,\theta) = a_{i1}x_1 + a_{i2}x_2 + a_{i3}x_3 + \ldots + A_{iN}X_N \quad i = 1,2,3 \ldots \ldots N$$

In this equation, x_j denotes the strength of the jth pixel in the image, and a_{ij} denotes the weight of the ray in pixel (j) that reached detector bin (i). This 2D projection is extended into 3D for CBCT using Siddon's algorithm, which is a technique for generating 3D projections [15]. This algorithm's execution is carried out by carrying out the following steps:

1. The scanned subject is divided into three orthogonal planes, N_X, N_Y, andN_Z.
2. The entry and exit points of the ray that penetrates the subject are determined by calculating the ray's intersection with the plane boundaries in each direction.
3. Determine the distribution of the plane indices between these lines
4. The voxel indices and section length of the ray inside each voxel (i.e., voxel weight) are computed.

The method is rotated after calculating the first projection at the first angle to obtain the next projection point at a different angle. In this study, we simulated the projection data for the optical Shepp-Logan head phantom (256*256*256) in the X, Y, and Z planes.

The Maximum Likelihood Expectation Maximization Imaging Technique

The Richardson-Lucy algorithm is another name for the MLEM algorithm, because Richardson and Lucy developed it in order to de-blur image applications [16] [17]. This algorithm is known as statistical iterative. In mathematical statistics there is a common iterative method known as the Expectation Maximization (or EM) Algorithm [18], the name of this technique originates from the fact that in each iteration there is an expectation step, that uses an estimation of the current parameter that is used to perform the reconstruction, followed by a maximum likelihood step that uses this reconstruction to adjust the estimate of the parameter [19].

In image restoration, the maximum likelihood technique is a realistic application of the EM process that works well where the projection data is incomplete [18]. Within the MLEM algorithm, the estimate of the image must fit the measured projections Eq. (1) expresses this algorithm [7].

$$x^{next} = x^{current} * \frac{\text{Backproject}\left\{\dfrac{\text{Measurment}}{Project\ (\mathrm{x}^{\text{current}})}\right\}}{\text{Backproject}\,\{1\}} \ldots\ldots\ldots\ldots\ldots (1)$$

The (1) in this equation is a vector of (1's). The vector has the same dimensions as the projection data vector. The uncertainty in the data is measured as a ratio rather than a discrepancy in this algorithm. The MLEM algorithm searches for the best solution (image) based on the projection data; Fig. (1) shows a diagram of this algorithm [20].

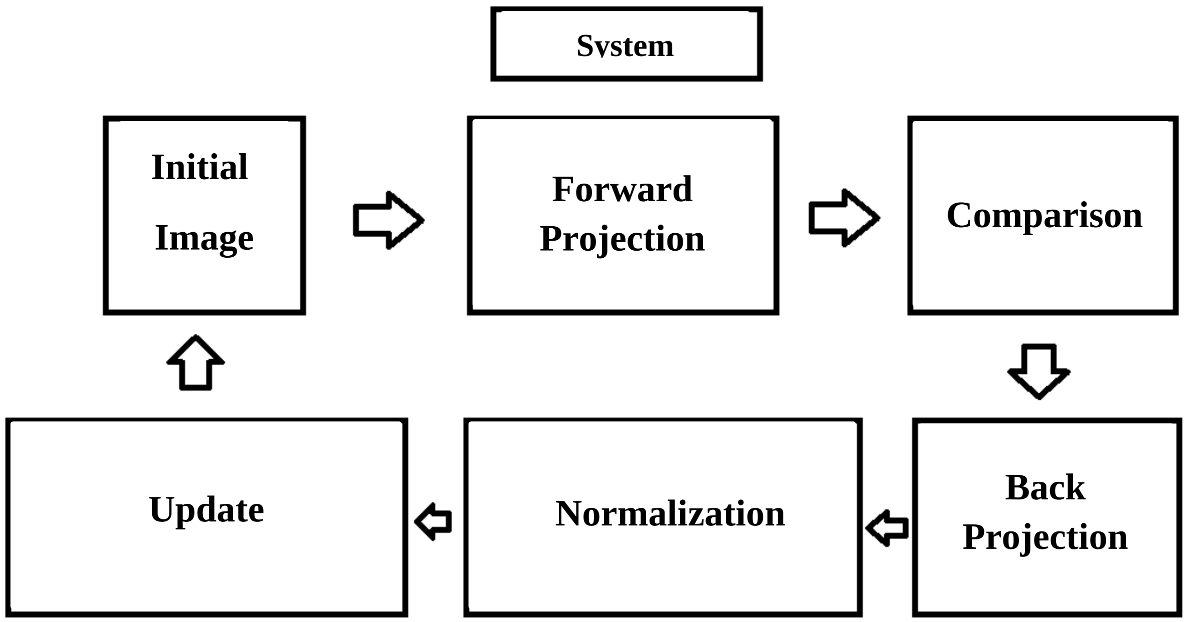

Figure (1) Diagram of the MLEM algorithm [20].

This figure demonstrates the MLEM reconstrucion process that is initated by generating an image estimate, simulating its projections, compairing them with the measured projections, then back-projectioning the result, normalizing the process, and finaly updating the image. These steps are repeated in each iteration.

Statistical iterative reconstruction algorithms have been proven beneficial in improving image quality [20]. In the MLEM algorithm, the objective function is defined first, then optimized. This algorithm seeks the best solution (image) based on the projection data. Eq. (2) [7] defines the iterations of the MLEM algorithm.

$$X_j^{next} = \frac{X_j^{current}}{\sum_i a_{ij}} \sum_i a_{ij} \left(\frac{p_i}{\sum_j a_{ij} \; X_j^{current}} \right) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (2)$$

Equation (2) is employed to update the pixel $(X_j^{current})$ of the initial image, by adding the back-projected effects of the contrast of the picture pixel's (j), calculated and simulated projections (j), for each projections ray (i). The result of this comparison then normalized using $(\sum_i a_{ij})$, which is a back projection of a vector of $(ones)$. This normalized pixel is used as a modification element that multiplies the current estimate of the image pixel with the original estimate of the image pixel to correct the current estimate of the image pixel, which is then used as the new initial image pixel in the next iteration [7].

Parallel Implementation of the MLEM Algorithm

While MLEM is a non-parallel reconstruction algorithm, it can be applied in parallel. In this study, we introduced a parallel computation method in the MLEM algorithm, which is used via vectorization and parallelization through CPU to speed up the volume Image reconstruction time. Vectorization is a digital technique that uses vector operations rather than loop-based operations on individual elements. In parallel computation, the automatic vectorization mechanism is a linear transformation that converts two-dimensional data into a one-dimensional vector. In other words, it is a compiler optimization that converts loops to vector operations. This procedure shortens the turnaround time. We implemented the proposed vectorization method in the MLEM by calculating projections to reduce the reconstruction time of the 3D image. The equations are used to update the weight of voxels in order to reconstruct the amount of images according to the MLEM algorithm's update equation Eq (2). The vectorization operation is carried out by reconstructing the MLEM algorithm using a Graphical-processing unit (GPU), which is described as a parallel, multithread, multi-core processor with enormous processing power. GPUs are used in the iterative reconstruction process because matrix-vector multiplication is the most time-consuming step in these algorithms. As seen in Fig. (2) [20] [21], huge collections of pixel weights and detector data could be mapped to parallel threads in GPUs and processed much faster than in CPUs.

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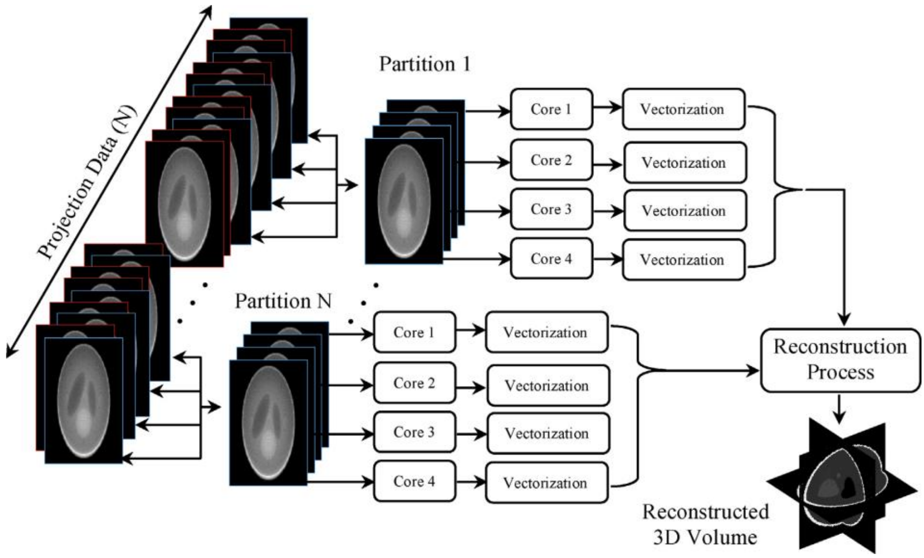


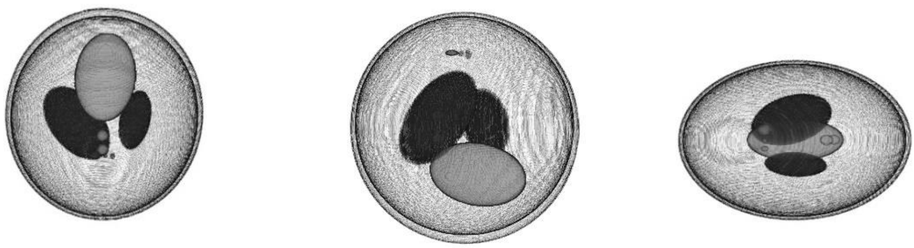
Figure (2) Parallelization of the projection data for 3D image reconstruction [21].

This diagram illustrates how running the MLEM algorithm on the GPU allowed parallel processing of large sets of pixels and projection results. This parallel method is a mode of operation in which an operation is divided into sections that are executed concurrently on separate processors connected to the same machine, allowing them to be processed even faster than CPUs. The algorithm would actually run quicker because it takes advantage of the GPU's high efficiency to speed the operation [20].

Results and discussion

Computing projection data

In this study, a one-degree rotation angle step is used. The size of the obtained projections was (256 * 256 * 360), where (256 * 256) is the size of the detector matrix and (360) is the number of projection angles. Figure (3) depicts three projections of a Shepp-Logan head phantom at three different angles of 0^0, 45^0 and 90^0. Figure (4) depicts the outcome of our planned solution. The findings show that creating the projection data took a long time. As a result, by using our suggested vectorization of the parallel method, we are able to reduce the time.



(a) **(b)** **(c)**

Figure (3) Cone-beam projections of a Shepp-Logan test phantom at the angles of (a) 0^0, (b) 45^0, and (c) 90^0

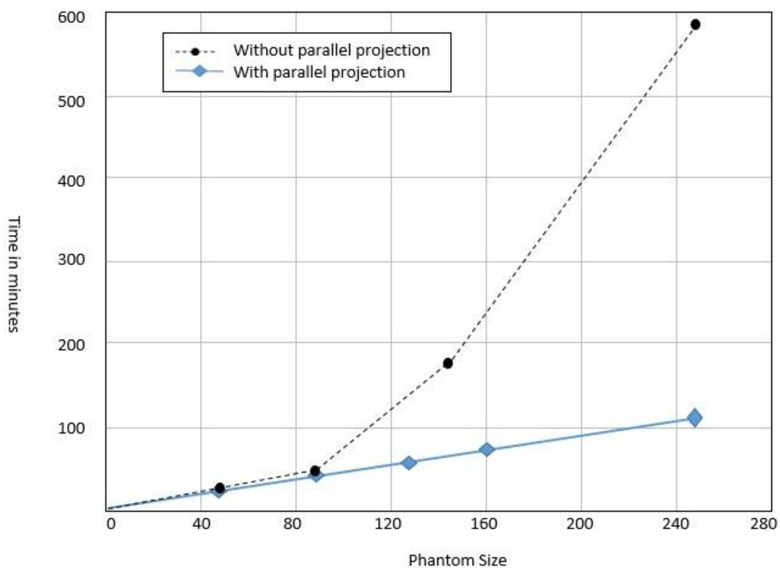


Figure (4) Effect of the parallel process on the projection generation time

The projection processing time of (360) views before the vectorization process takes (7.97) hours with a phantom of (256 *256 *256), but it takes (30.51) minutes with the parallel process. This projection data are used as raw inputs in the reconstruction process to generate 3D images.

Results of the Reconstruction Process

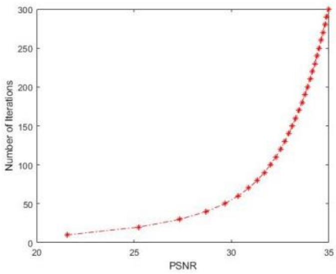
The reconstructed slices of the 3D phantom test image from our rapid parallel MLEM algorithm are illustrated in Fig. (5)

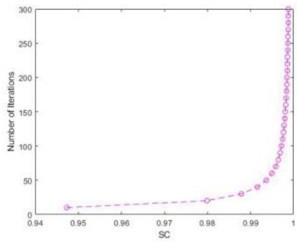
Figure (5) The reconstructed Shepp-Logan phantom images Using the parallel MLEM algorithm (a) Axial, (b) Coronal, and (c) Sagittal

The quantitative research efficiency assessment of the reconstructed images is seen using a Peak Signal to Noise Ratio (PSNR), Root Mean Square Error (RMSE), and Structural Content (SC) [23].

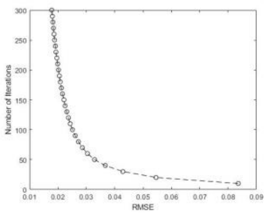
Effect of the Number of Iterations on the MLEM Algorithm

The statistical iterative MLEM technique depends on two values, specifically the relaxation parameter and the number of iterations. The relaxing factor should be changed to a value between 0 and 1. We decided, on the other hand, to investigate the influence of the number of iterations parameter for the values (0, 10, 20, 30,... 300) with a fixed relaxation parameter of (1). The consequence of the number of iterations is depicted in Fig. (6) on the performance in term of the PSNR, RMSE, and SC. The results show that in the case of parallel and the non-parallel MLEM technique, increasing the iteration number leads to a reduced value of the RMSE, which is a measure of the average magnitude of the error, and increase the PSNR and SC, which measures the peak error and establishes the degree to which images match each other respectively.





(a) (b)



(c)

Figure (6) Impact of increasing the number of iterations on (a) PSNR, (b) SC, (c) RMSE

These findings show that increasing the number of iterations improves the accuracy of the restored picture thus lengthening the reconstruction process.

The Reconstructed 3D Image's Quality

The reconstruction technique's findings using the full scan projections details of the Shepp-Logan phantom are seen in Fig (5). The findings reveal the restored volume's coronal, sagittal, and axial slices. In terms of image accuracy, the Traditional MLEM approach performs similarly to the Parallel MLEM. The calculation time of these methods differs significantly, as seen in Table (1).

Table (1) Image quality measurements using the parallel and non-parallel MLEM algorithm.

View	RMSE	PSNR	SC
Axial	0.2569	11.8061	0.8311
Coronal	0.2695	11.3877	0.8833
Sagittal	0.2505	12.0242	0.7560

Conclusion

In this article, we demonstrated a quick version of the MLEM algorithm using parallel computing and defined its success for CBCT. The results show that the reconstructed images provided by the MLEM take less time to recreate. Even with a small amount of projection results, our parallel method performs well. Since a lower volume of projection data means a shorter scanning period, it often indicates a lower radiation exposure. As a result of our study, we were able to have a better image reconstruction method with superior accuracy, faster computation time, and fewer projection data, which reduced the necessary radiation exposure. The MLEM solution discussed here could be a better image restoration technique for CBCT in clinical applications.

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