Reconstruction of Region-of-interest Image in Narrow-field-of-view Computed Tomography without Prior Constraints

Esmaeil Enjilela* Esam M. A. Hussein

Laboratory for Threat Material Detection, Department of Mechanical Engineering, University of New Brunswick, Fredericton, NB, E3B 5A3 Canada

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Abstract

This paper presents a numerical method for reconstructing a tomographic image for a region of interest (RoI) within a section using narrowed radiation beams to reduce radiation exposure. The RoI image reconstruction is formulated as a discrete problem to avoid the truncated (incomplete) problem associated with the conventional analytic filtered backprojection method. This in turn allows local reconstruction of RoI images without any prior information or constraints. A coarse image of the entire section is first reconstructed with the aid of a modified convex maximum likelihood (MCML) algorithm. The coarse image is then used to account for the effect of the RoI surroundings. With RoI-specific projections, an RoI image is then reconstructed, with either the MCML or conjugate gradient methods, at the desired pixel size. The proposed method is evaluated using an anthropomorphic FORBILD head phantom, showing an image quality comparable to that of conventional computed tomography, but with a ~69% reduction in radiation exposure. Unlike existing approaches that require some prior knowledge of a segment of the image, this approach does not require any prior image information and imposes no constraints on the solution.

Keywords: Computed tomography (CT), Region of interest (RoI), Truncated projection (TP), Reconstruction algorithm (RA)

1. Introduction

Computed tomography (CT) produces slice (section-by-section) images of an object. However, it is often desired to reconstruct a tomographic image for a particular region of interest (RoI), such as the heart. This can be accomplished by confining radiation exposure to a narrow field of view (FoV) aimed at the RoI, to accentuate its presence. This, however, analytically results in so-called truncated projections (TPs). Approaches introduced to deal with this TP problem include: (1) estimation of missing ray sums in projections outside the RoI, (2) relying on a previously acquired global (section) image to correct for the effect of the RoI surroundings, (3) incorporation of some knowledge about the RoI or its surroundings into the image reconstruction process, and (4) optimizing the solution for best elucidation of the RoI within a global image.

Missing data outside an RoI have been estimated via linear extrapolation of available ray sums in each projection [1,2] and using assigned nominal or known material outside the RoI [3,4]. Other researchers acquired a limited number of ray sums outside the RoI and interpolated them to generate the missing data [5-7]. Researchers sampled coarse projections outside the RoI to provide the missing ray-sum projections. These approximations that can lead to error if the outside of the RoI is not highly homogeneous.

A previously acquired global (full-section) image can be used to compensate for missed ray sums in TPs. Ruchala et al. [10] took advantage of the availability of a previously acquired full-section image for treatment planning to correct for missed ray sums in subsequent RoI images for monitoring progress in treatment. Prior images may not always be available, and must be well aligned with the section for which RoI imaging is to be performed.

Known values of image attributes within some “tiny” (small) areas within an RoI [11,12], or even outside it but in the path of the recorded projections [13], are employed when image reconstruction relies on the finite Hilbert transform. The inverse of this transform leads to a solution in terms of some arbitrary constant, the arbitrariness of which is removed by the known attributes. For details, see the excellent review published in the literature [14]. It is not, however, always possible to have knowledge of image attributes.

The premise that medical images tend to be piecewise-constant (smooth) within distinct sub-regions [15] was
exploited for RoI narrow FoV imaging. Given that the first spatial derivative of image attributes tends to be equal to zero within smooth regions and non-zero at their boundaries, the domain of this derivative tends to be sparse. Therefore, when the first norm, \( \| \cdot \|_1 \), of image attributes between iterations is minimized via the total variation method [16], an optimal solution within a confined RoI is obtained. Yang et al. [17] relaxed this sparseness condition by assuming that the image attributes within the RoI vary according to some polynomial functions.

Both the finite Hilbert transform approach and the total variation method perform image reconstruction over an entire section, producing an RoI image with the same resolution as that of the rest of the global image. Given the limited number of available (truncated) projections, this global image needs to be reconstructed over relatively large-size pixels, e.g., \( 1 \times 1 \text{ mm}^2 \) [15,16], a size larger than \( 0.5 \times 0.5 \text{ mm}^2 \) typically desired in clinical applications [18].

The present study proposes a matrix-based solution method for RoI image reconstruction from TPs. This method does not demand any \textit{a priori} knowledge or features regarding the nature of the image and does not impose any constraints on the solution. Furthermore, since image reconstruction is performed within the RoI alone, one can utilize the small pixel size desired in medical imaging.

2. Mathematical formulation

Analytic continuous formulations and solutions dominate image reconstruction in computed tomography (CT) because of their computational efficiency. However, image reconstruction is a discrete problem, since the image is formed over finite pixels or voxels. The algebraic reconstruction technique (ART), which was used in earlier CT systems [19], is a discrete solution. Such discrete problems can be posed in matrix form, but the huge size of the system matrix (tens of thousands of rows and columns) discouraged its use. Given, however, the relatively small size of an RoI, the advancement of computing power, and the availability of robust iterative-based matrix inversion techniques, matrix formulation is applied here for RoI image reconstruction from TPs, which do not lend themselves naturally to solution by analytic formulations, as indicated in Section 1. This study shows that the matrix formulation of the image reconstruction problem from TPs is quite straightforward.

Let us consider a narrow-FoV arrangement, in which a radiation field covers an RoI and rotates around it in \( 2\pi \) (the center of the entire object is still the center of rotation), providing many discrete projections. Although source rays are confined and targeted to the RoI, they traverse the region outside of it, and as such carry information on the RoI’s surroundings. In this arrangement, the presence of the RoI is masked by its surroundings, but is also accentuated by being exposed more often to radiation than its surroundings. However, as radiation travels towards and away from the RoI, it carries information on the material outside of the RoI, which can be used to overcome the masking effect. Since what is needed from the outside of an RoI is its overall (integral) contribution to the recorded projections, there is no need for detailed (fine-pixel) information outside the RoI. Therefore, the problem is formulated in a way that enables the reconstruction of a coarse global (full-section) image, from which the contribution of the region of the RoI on measurements is estimated.

Two overlapping pixel grids are used: a fine grid within the RoI with \( N \) small pixels with a size equal to that clinically desired and a coarser grid with \( n \) larger pixels covering the entire section. Then, any projection, ray sum, \( p_r \), can be expressed in discrete form, guided by Fig. 1, as given by the equations below.

![Schematic showing a projection, \( p_{\phi}(r, \theta) \), and a ray sum in a narrow-FoV exposure directed towards RoI with \( \mu \) and \( \lambda \), respectively, for the image attributes (attenuation coefficients) within and outside the RoI, with \( \phi \) indicating orientation angle for radiation source. The narrow FoV is centered on RoI.](image)

Within the fine grid over an entire section with \( N \) pixels:

\[
\mathbf{p}_i = \sum_{j=1}^{N} \mu_j \Delta R_i
\]

where \( \mu_j \) is the value of the attenuation coefficient (image attribute) averaged over a small pixel \( j \), and \( \Delta R_i \) is the distance traveled by ray \( j \) in pixel \( i \).

Within the coarse grid over an entire section with \( n \) pixels:

\[
\mathbf{p}_i = \sum_{k=1}^{n} \lambda_k \Delta R_i
\]

where \( \lambda_k \) is the value of the attenuation coefficient averaged over a larger pixel \( k \), and \( \Delta R_i \) is the distance traveled by ray \( j \) in pixel \( k \). The summation over the fine grid within the RoI and the coarse grid outside it is expressed as:

\[
\mathbf{p}_i = \sum_{j=1}^{N} \mu_j \Delta R_i + \sum_{k=1}^{n} \lambda_k \Delta R_i
\]

where \( N \) is the number of small pixels in the RoI and \( n \) is the number of large pixels outside the RoI. Equations (1.a), (1.b), and (1.c) take, respectively, the matrix forms:
where \( \mathbf{A} \) is an \( M \times N \) system matrix for the fine grid, \( M \) is the total number of ray sums collected over all directions, \( \mu, \subset \mu \) are the elements of \( \mu \) inside the RoI, \( \mu, \subset \mu \) are those outside the RoI, and \( \mathbf{A}, \mathbf{A} \) are submatrices of \( \mathbf{A} \) that relate \( \mathbf{P} \) to \( \mu, \) and \( \mu, \) respectively.

\[
\mathbf{P} = \mathbf{A} \mu = [\mathbf{A},; \mathbf{A},] \begin{bmatrix} \mu, \\ \mu, \end{bmatrix}
\]

(4)

where \( \mathbf{B} \) is an \( M \times n \) matrix for the coarse grid, and \( \lambda, \subset \lambda \) are the elements of \( \lambda \) inside the RoI, \( \lambda, \subset \lambda \) are those outside the RoI, and \( \mathbf{B}, \mathbf{B} \) are submatrices of \( \mathbf{B} \) that relate \( \mathbf{P} \) to \( \lambda, \) and \( \lambda, \) respectively.

\[
\mathbf{P} = \mathbf{B} \lambda = [\mathbf{B},; \mathbf{B},] \begin{bmatrix} \lambda, \\ \lambda, \end{bmatrix}
\]

(5)

where \( \mathbf{A}, \subset \mathbf{A} \) is the image attributes within the RoI, \( \lambda, \subset \lambda \) is those outside it, \( \mathbf{A}, \) is an \( M \times N \) matrix (a submatrix of \( \mathbf{A} \)) for the fine grid within the RoI, and \( \mathbf{B}, \mathbf{B} \) is an \( M \times n \) matrix (a submatrix of \( \mathbf{B} \)) for the coarse grid outside the RoI.

It is obvious that the solution of Eq. (2.b) provides a solution for \( \lambda, \subset \lambda \). Having the solution for \( \lambda, \) from Eq. (2.b), Eq. (2.c) provides the solution for \( \mu, \). Note also that, a solution for \( \mu \) can be found from Eq. (2.a), but then due to the large number of pixels, the problem may be poorly determined and susceptible to noise because with narrow-FoV exposure, the number of available measurements can be less than the number of unknowns (pixel attributes). It should be kept in mind that the solutions for Eqs. (2.a) or (2.b) are over pixels which correspond to material exposed to radiation, i.e., they are not for areas, if any, outside the RoI that are not covered by radiation. The formulations of (2.b) and (2.c), unlike the methods reviewed in Section 1, do not require approximating the value of the missing ray sums, or knowing in advance the attributes of any regions in the image. In addition, the proposed approach does not demand piecewise-constant image features. Furthermore, since image reconstruction in Eq. (2.c) is within an RoI alone, one can utilize the smaller pixel size typically desired in medical applications even with the limited number of measurements provided by the TPs. With the coarse solution of Eq. (2.b) and with a fine solution only within the RoI from Eq. (2.c), the matrix size for each solution becomes readily manageable. This also allows the use of powerful matrix-based methods, such as those of the maximum likelihood and conjugate gradients, which are known for their ability to provide better image contrast than that obtained using analytic methods [20].

3. Numerical implementation

The direct matrix solutions of (2.b) and (2.c) require the inversion of \( \mathbf{B}, \mathbf{B} \) and \( \mathbf{A}, \mathbf{A} \), respectively. The resulting matrices are in practice too huge to directly invert. Moreover, the inverse radon transform problem in CT is ill-posed, and consequently the corresponding discretized problems of the matrix equations of (2.b) and (2.c) are ill-conditioned. This necessitates the employment of iterative numerical algorithms that are not susceptible to noise propagation and can introduce solution regularization. Note that the widely used filtered backprojection (FBP) method is not suited for global (full-section) image reconstruction with TPs because it would produce an incorrect image [8]. For these reasons, the modified convex maximum likelihood (MCML) algorithm of Fessler [21] [Eq. (1.68)] was first selected since it does not require full narrow-FoV projections, and as such it can be used in solving the full-section global problem of (2.b). Moreover, the degree of concavity of the log-likelihood in this algorithm is modified to enhance its convergence rate [21]. The MCML algorithm also preserves the expected non-negativity of the solution [21], while introducing some regularization to control noise propagation. In addition, the MCML algorithm has low memory storage demands because it can be implemented utilizing the fact that matrices \( \mathbf{B} \) and \( \mathbf{A} \) are heavily sparse, since a radiation ray passes only through a fraction of all pixels. However, like all maximum likelihood iterative methods, the MCML method modifies the estimated solution gently from one iteration to another, which leads to image smoothing (a form of solution regularization). Such smoothing can be tolerated in the global problem of (2.b), but can suppress sharp changes in the desired finer RoI image obtained by solving Eq. (2.c). Therefore, for the latter, the conjugate gradient (CG) algorithm of MATLAB 7.11.0 [22] is adopted. Although, it is a computationally demanding scheme, it can be accommodated when image reconstruction is confined to the smaller RoI. Nevertheless, for sake of comparison, both the MCML and CG algorithms are used for RoI image reconstruction. With a solution for \( \lambda, \) available from Eq. (2.b), one can argue that RoI image reconstruction is no longer a truncated problem, since its outside is known, and the widely used FBP method can be utilized. However, due to the inherent susceptibility of the FBP reconstruction method to noise [20] and the expected increase in error caused by the presence of the \( \mathbf{B}, \lambda, \) term in Eq. (2.c), FBP is expected to produce a poor RoI image, as demonstrated in Section 5.

The convergence of iterative MCML and CG algorithms can be monitored by the following metric:

\[
\delta^{(k)} = \left( \frac{\mu^{(k)} - \mu^{(k-1)}}{N} \right)
\]

(7)

where \( \mu^{(k)} \) is the matrix of the reconstructed image parameter at iteration \( k, \) \( N \) is the number of image pixels, and \( || \) denotes a Euclidean norm.

The measurement metric was also introduced to measure how close \( \mu^{(k)} \), calculated for a solution \( \mu^{(k)} \), is to the input image projections, \( \mathbf{P} \), given by:

\[
\delta_p^{(k)} = \left( \frac{\mu^{(k)} - \mathbf{P}}{||\mathbf{P}||} \right)
\]

(8)

Furthermore, image resemblance between a reconstructed image at iteration \( k, \) \( \mu^{(k)} \), and the actual \( \mathbf{P} \) can be measured
4. Experimental setup for numerical testing

In order to test the proposed numerical schemes, a typical CT system was simulated and noisy measurements were synthesized for ROIs in a standard phantom. The quality of reconstructed ROIs was assessed by measuring their material contrast and spatial resolution (point spread function). The reconstructed narrow-FOV images were also compared to ROI images extracted from conventional wide-FOV full-section images reconstructed with the common FBP method to determine whether the proposed numerical processes produce equivalent image quality.

4.1 CT system

A typical third-generation CT system was simulated with the aid of an image reconstruction toolbox [24]. This system incorporated a fan beam, positioned at 541 mm from the center of the imaging domain. For full-FOV imaging, the fan beam angle was 56°. However, it was assumed that the opening angle of the beam is adjustable so that it can cover the width of an ROI at its closest distance to the source. Detectors, each 0.5 mm in width, were located on an arc of a 949-mm radius centered at the source. Each detector was offset by 0.125 mm from the line connecting the source’s focal spot and its rotation axis. A photon equivalent energy of 60 keV was assumed in this work (representative of X-rays employed in medical imaging [19,25,26]) to avoid the complicated process of assigning a single attenuation coefficient to a material exposed to a monochromatic X-ray source, as was done for example in [26]. A Gaussian noise of 5%, approximating Poisson counting statistics, typical of CT systems [27], was introduced into the synthesized intensity measurements. Results in the absence of noise and in the presence of extreme noise (10%) are reported elsewhere [23].

4.2 Test phantom and image quality

A standard FORBILD head phantom [28] was simulated. The phantom, shown in Fig. 2, includes a depiction of the calotte (\( \mu = 0.04499 \) mm\(^{-1} \)), frontal sinus (\( \mu = 0 \) mm\(^{-1} \)) and surrounding bones (\( \mu = 0.04499 \) mm\(^{-1} \)), petrous bone (\( \mu = 0.04499 \) mm\(^{-1} \)), inner ears (\( \mu = 0 \) mm\(^{-1} \)), eyes (\( \mu = 0.02134 \) mm\(^{-1} \)), as well as homogeneous brain matter including grey matter (\( \mu = 0.02096 \) mm\(^{-1} \)), ventricle (\( \mu = 0.02058 \) mm\(^{-1} \)), subdural hematoma (\( \mu = 0.02116 \) mm\(^{-1} \)), and lumps (bottom left: \( \mu = 0.02201 \) mm\(^{-1} \); bottom right: \( \mu = 0.01991 \) mm\(^{-1} \)). Note that the attenuation coefficients of the head phantom components, \( \mu \), are at a 60-keV effective X-ray energy [29,30]. The phantom was simulated within a 256 × 256 mm\(^2 \) frame, whose width is equal to the length of a transaxial section of an adult head [26]. To assign material attributes and synthesize measurements, the phantom was initially configured

\[
\delta_{\text{ROI}} = \frac{[\hat{\mu}^\text{ROI} - \mu]}{\mu} \tag{9}
\]

Note that the image metric is only available for testing purposes, since the actual image is unknown in reality.

One remaining aspect of the numerical implementation process is to determine the pixel size for the global problem of (2.b) and (2.c). For the latter, the pixel size is pre-determined by the number of projections directed to the ROI. Typically, the total number of measurements (ray sums) is at least three times the number of pixels in a section image [18] to over-determine the problem and reduce the effect of noise. For the coarse global image reconstruction problem of (2.b), one has some flexibility in choosing the pixel size, since this is only a step in solving the ROI problem of (2.c). However, in accordance with the current practice in CT imaging, the size of the pixel is chosen for the coarse global problem so that a degree of over-determination of three or more is preserved. The effect of the coarse image’s pixel size on ROI image reconstruction has been previously studied [23]. All calculations in this study were performed using a SunFire × 4600 M2 machine with 64 GB of RAM and a dual-core AMD Opteron 3.2-GHz CPU.

Figure 2. Head phantom [28] (gray scale: [−1000,1000] Hounsfield units (HU)). (a) Actual configuration with designated ROI (circled), (b) details of ROI in (a) with two high-contrast (1 and 2) 0.25 × 0.25 mm\(^2 \) inserts to measure the spatial resolution, and four square areas (a, b, c, d), forming pairs, for material-contrast determination (magnified in side images with [0,50] HU gray scale). Small side images are magnified images, extended in gray scale to show the spread of high-contrast inserts.

with 0.25 × 0.25 mm\(^2 \) elements, smaller than the 0.5 × 0.5 mm\(^2 \) pixel size typically used in medical applications. One circular region with a diameter of 70 mm close to the center was designated as an ROI. The location of this near-center ROI allows assessment of the proposed scheme when an ROI is heavily masked by its surroundings. Here, the location and size of the ROI are assumed to be known, but in practice this may be determined from a prior image or from body anatomy. With known ROI location and size, radiation exposure can be confined to the ROI. The FoV for a narrow beam must be such that it
arrangement results in a radiation exposure of only 30.6% that of what would have been required in a typical full-FoV image reconstruction.

Table 1. Image quality metrics for reconstructed images for RoI in Fig. 3.

<table>
<thead>
<tr>
<th>Image</th>
<th>Measurement metric (δ_{μ,σ})</th>
<th>Image metric (δ_{μ,σ})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extracted from full-FoV FBP</td>
<td>0.1237</td>
<td></td>
</tr>
<tr>
<td>FBP RoI reconstruction</td>
<td>0.0019</td>
<td>0.1675</td>
</tr>
<tr>
<td>MCML RoI reconstruction</td>
<td>0.05000</td>
<td>0.1311</td>
</tr>
<tr>
<td>CG RoI reconstruction</td>
<td>0.00029</td>
<td>0.1167</td>
</tr>
</tbody>
</table>

(b) Contrast resolution (C')

<table>
<thead>
<tr>
<th>Image</th>
<th>Spatial resolution: FWHM (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extracted from full-FoV FBP</td>
<td>0.0839</td>
</tr>
<tr>
<td>FBP RoI reconstruction</td>
<td>0.0804</td>
</tr>
<tr>
<td>MCML RoI reconstruction</td>
<td>2.6590</td>
</tr>
<tr>
<td>CG RoI reconstruction</td>
<td>1.4767</td>
</tr>
</tbody>
</table>

(c) High-contrast: FWHM (mm)

<table>
<thead>
<tr>
<th>Image</th>
<th>Pair area, see Fig. 2(b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>x direction</td>
<td>y direction</td>
</tr>
<tr>
<td>1st</td>
<td>2nd</td>
</tr>
<tr>
<td>Extracted from full-FoV FBP</td>
<td>0.5005</td>
</tr>
<tr>
<td>FBP RoI reconstruction</td>
<td>0.5005</td>
</tr>
<tr>
<td>MCML RoI reconstruction</td>
<td>0.5755</td>
</tr>
<tr>
<td>CG RoI reconstruction</td>
<td>0.5914</td>
</tr>
</tbody>
</table>

With 244,800 available ray sums, one has sufficient data to reconstruct a full-section global image with a pixel size of 1 × 1 mm² and a degree of overdetermination of 3.73, larger than the typical value of three. This allows a pixel size of 1 × 1 mm² (256 × 256 pixels) for use in global reconstruction, four times larger than the pixel size of 0.5 × 0.5 mm². However, the purpose of reconstructing the global image is not to produce a full-section image, but to facilitate the solution of Eq. (2.c) to produce an RoI image.

The MCML algorithm was used to reconstruct a global coarse image. This image is not shown here as it was only used to calculate λ_{o}, required in Eq. (2.c). The attenuation coefficient of water, μ = 0.02046 mm⁻¹ at the effective X-ray energy of 60 keV, was employed as an initial estimate for the MCML algorithm. The iterative process was stopped after 100 iterations, at which the convergence metric of Eq. (3.a), δ_{μ,σ}^o, approached 6.5 × 10⁻¹³ (nearly zero) and the measurement metric of Eq. (3.b), δ_{σ}^o, stabilized at a value of 1.9 × 10⁻². From the results of the global image reconstruction, the λ_{o} values required in Eq. (2.c) were extracted. The vector B_λ was then used to calculate a new vector p_B_λ, and the subsequent solution of Eq. (2.c) for μ_0, which constituted the RoI image. This solution was obtained using the three methods of FBP, MCML, and CG for comparison.

Figure 3 shows the RoI images reconstructed for this RoI,
with a pixel size of $0.5 \times 0.5 \text{ mm}^2$. For sake of comparison, the actual RoI image and the RoI extracted from the full-FoV FBP reconstructed image (Section 4.3) are shown in Figs. 3(a) and 3(b), respectively. Note that the extracted image, as well as all other reconstructed images reported here, are raw images, i.e., it is the direct result of image reconstruction without any image post-processing enhancement applied.

![Image](a)

![Image](b)

![Image](c)

![Image](d)

![Image](e)

Figure 3. Images of RoI designated in FORBILD head phantom of Fig. 2(a) (gray scale: [-1000, 1000] HU). (a) Actual RoI and those (b) extracted from full-FoV FBP (5% noise, $0.5 \times 0.5 \text{ mm}^2$ pixels) and reconstructed using (c) FBP ($0.5 \times 0.5 \text{ mm}^2$ pixels), (d) MCML ($0.5 \times 0.5 \text{ mm}^2$ pixels), and (e) CG ($0.5 \times 0.5 \text{ mm}^2$ pixels).

The FBP RoI image in Fig. 3(c) was reconstructed with a ramp filter [25] with a CPU time of 17.25 seconds and a memory usage of 0.3125 GB. One can see that FBP was able to resolve the main attributes of the RoI image, i.e., the frontal sinus and its surrounding bones and grey matter. The presence of the eyes, however, was neither resolved in the FBP RoI nor the full-FoV FBP reconstructions; compare Figs. 3(b) and 3(c) with the actual image of Fig. 3(a). This is because the eye has an attenuation coefficient that differs by only 1.81% from that of the background tissue (grey matter), which was masked by the 5% measurement noise. The overall difference between the reconstructed and actual image, as given by the image metric, is larger in the FBP RoI image than in the extracted image from the full-FoV FBP reconstruction: $\delta_\mu = 0.1675$ versus $\delta_\mu = 0.1237$, as listed in Table 1. This difference is demonstrated in more detail by comparing the profiles of the $\mu$ values of pixels in the image, as shown in Fig. 4, in which the values in the RoI images are plotted along a dotted line in the RoI depicted at the top for this figure. The FBP RoI reconstructed image shows the most fluctuating behavior. This image also exhibited the poorest contrast among all images. Nonetheless, as Table 1(a) shows, the spatial resolution of the FBP RoI image was comparable with that of the extracted image from the full-FoV FBP method. This overall poor quality of the FBP RoI image was expected due to the uncertainty associated with the process of calculating the RoI-specific projections and the susceptibility of the FBP reconstruction method to noise. With appropriate filtering, the performance of the FBP reconstruction method may be improved, but the selection of such filtering can be dependent upon the attributes of an imaged object and the RoI. As such, the FBP method is not recommended for RoI image reconstruction.

![Image](a)

![Image](b)

Figure 4. Profile of $\mu$ values along the line shown in the top RoI image for actual image, image extracted from full-FoV FBP, and RoIs reconstructed from narrow-FoV FBP, MCML, and CG.

The MCML RoI image of Fig. 3(d) was recorded after 37 iterations, when the convergence metric, $\delta_{\mu}^{37}$, approached almost zero and the measurement metric, $\delta_{\mu}^{37}$, began to stabilize. The MCML RoI image was produced with a CPU time of 234.48 seconds and memory usage of 0.731 GB. Visually, one can see in Fig. 3(d) that the MCML RoI reconstruction was also able to resolve all the main components of the RoI, such as the sinus, its associated bones, and grey matter. The image metric, $\delta_\mu$, of the MCML RoI image is comparable with that of the extracted image from the full-FoV FBP reconstruction: 0.1311 versus 0.1237, as given in Table 1(a). Improvement in the image metric for MCML RoI versus that of the FBP RoI reconstruction (0.1331 versus 0.1675) can be attributed to the smooth progress of the MCML algorithm from one iteration to another. The contrast resolution,
however, was higher for the MCML RoI image, (e.g. 2.6590 versus 0.0839 for the a-b contrast-pair areas); see Table 1(b) for C values. Furthermore, from Table 1(c), one can see that the spatial resolution for the MCML RoI image is fairly comparable with that of the extracted image from full-FoV FBP, but varies slightly with the x and y directions.

The reconstructed CG RoI image for the studied RoI is shown in Fig. 3(e). This image was recorded after ten iterations, when the convergence metric was quite small, \( \delta^{\text{con}} = 2.3 \times 10^{-6} \), and the measurement metric, \( \delta^{\text{meas}} \), almost stopped declining. The CG algorithm required a CPU time of 25.10 seconds and a memory usage of 1.969 GB. The CG algorithm was able to well match the projections of the reconstructed image with the input RoI-specific projections, as indicated by the very small \( \delta^{\text{con}} \) value (0.029%) in Table 1(a). The CG RoI algorithm provided slightly better overall resemblance between the CG RoI image and its counterpart in the actual image relative to the extracted image from full-FoV FBP; 11.67% versus 12.37%, see Table 1(a). This is further confirmed by the image profile of Fig. 4, which shows that the CG reconstructed attributes better match the sharp changes, associated with the presence of bones, than the other methods. The edge-matching ability is peculiar to the CG method because of its better ability to estimate gradients. The contrast resolution of the CG RoI image was even better for the measured contrast-pair than those of their counterparts in the full-FoV FBP image (e.g., 1.4767 versus 0.0839) but less than that of the MCML RoI image (2.6590), as shown in Table 1(b). This is visibly reflected by the distinct appearance of sinus bones, the frontal sinus, and grey matter. The spatial resolutions of the CG RoI image for all high-contrast inserts were larger than the pixel size (e.g., 0.5914 and 0.5664 versus 0.5 mm in the x and y directions for the 1st high-contrast insert), but it is still comparable with those of the high contrast inserts in the extracted image from the full-FoV FBP reconstruction.

Overall, the quality of images produced by the MCML and CG methods for the RoI was fairly comparable with that of the images extracted from a global reconstruction by FBP with full-FoV radiation exposure. On the other hand, FBP produced a poor RoI image (in terms of contrast resolution, C, and image metric, \( \delta_{\text{meas}} \)), and is thus not recommended for use in RoI image reconstruction, at least with the proposed method. It should be also noted that these RoI images were obtained from narrow-FoV exposure with a 69.4% reduction in radiation exposure in comparison to that for full-FoV imaging. Similar trends were also observed in other studies of this methodology (e.g., [23]).

6. Conclusion

This paper demonstrated that with a narrow-FoV exposure, one can reconstruct an image for an RoI without any constraints or prior image information, but with the aid of a coarse solution of the global problem. This was made possible via a discrete formulation of the problem that segregated it into a coarse global (full-section) problem and a local finer (RoI) problem. In order to deal with the ill-conditioning of the resulting inverse problem, iterative inversion techniques were utilized, namely the MCML algorithm and the CG method. The proposed methodology was numerically tested for an RoI within a section in the standard FORBILD head phantom. The results show that the reconstructed RoI images are comparable in quality to those extracted using the conventional (but more radiation exposure demanding) full-FoV FBP method.

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References


