Computed Tomography Resolution Enhancement by Integrating High-Resolution 2D X-Ray Images into the CT reconstruction

Steffen KIESS 1, Jajnabalkya GUHATHAKURTA 1, Jürgen HILLEBRAND 1, Julia DENECKE 2, Ira EFFENBERGER 2, Sven SIMON 1

1 Institute for Parallel and Distributed Systems, University of Stuttgart; Stuttgart, Germany
Phone: +49 711 685 88396, Fax: +49 711 685 78396; e-mail: Steffen.Kiess@ipvs.uni-stuttgart.de
2 Fraunhofer Institute for Manufacturing Engineering and Automation; Stuttgart, Germany

Abstract
The resolution of computed tomography of flat structures (e.g. printed circuit boards) is limited by the need to rotate the object by at least 180 degrees. 2D X-ray images can achieve higher resolutions but show only a part of the object and contain data for several different layers, making it hard to do further image processing steps like edge detection. This paper presents an approach which acquires both a standard CT image data set and a set of high-resolution 2D images, which are taken with the object much closer to the source, and then merges these data sets by using them as input for an iterative reconstruction algorithm. The resulting high-resolution voxel data set provides high-resolution information in directions parallel to the structure and, unlike the raw 2D images, the layers are separated. The approach presented here is verified using a simulated data set of a printed circuit board with line pair structures and an edge used for determining the modulation transfer function. The improvement of the resolution achieved with this approach is roughly 4.5 for the considered test structure.

Keywords: CT, multi-angle radiography, image processing, high-resolution, data fusion

1. Introduction
The resolution of a CT scan depends on the distance between the X-ray source and the object; when this distance decreases, the geometric magnification and therefore the resolution increases. The achievable resolution is limited by the need to rotate the object by at least 180 degrees. For planar objects (e.g. printed circuit boards), it is possible to get a significantly higher resolution for 2D images, as it is possible to bring the object much closer to the X-ray source. However, if the object contains several layers, the resulting images will contain an overlay of all the layers in the object.

This paper presents a method to combine the low-resolution CT data and the high-resolution 2D data to produce a 3D data set where the individual layers of the object are separated but the high resolution parallel to the layers is retained. The method is based on performing an iterative reconstruction of the data using the maximum likelihood expectation maximization (MLEM) [1] technique and using both the low-resolution images for the CT and the high-resolution images as input data. Acquiring the images for this method is shown in Section 2, the reconstruction is shown in Section 3.

In order to verify the presented method, it has been applied to a set of simulated CT images of a printed circuit board (PCB) containing line-pair structures in Section 4. The improvement of the spatial resolution achieved by using the resolution enhancement method is measured using the modulation transfer function (MTF) and the contrast of line pairs, similar to [2].

2. Image Acquisition
The resolution enhancement method consists of three steps: First, a normal CT data set is acquired (see Section 2.1). Then, the object is moved closer to the source and a set of high-resolution 2D images is acquired (see Section 2.2). Then the data acquired in the first and in the second step is merged by using an iterative reconstruction algorithm (see Section 3).
2.1 CT

The first step is to record a standard CT data set (see Fig. 1a). For this the object is rotated by 360 degrees and the source-object distance is chosen large enough so that while rotating the object the entire object always stays visible on the detector.

The data acquired in this step provides only low-resolution information but contains images from all angles and therefore allows separating the data into several layers.

2.2 High-resolution 2D images

The next step is to create the high-resolution 2D images (see Fig. 1b). For this step the object is moved significantly closer to the X-ray source. Because the object is perpendicular to the line connecting the X-ray source to the detector, the source-object distance can be chosen as low as 1 cm. This allows recording images with a very high resolution, however only a small part of the object will be visible in the image. In order to get data for the entire object, multiple images are done while moving the object in a grid-like fashion along the X and Y axes orthogonal to the source-detector axis. The step size for taking the images should be taken small enough so that the images are overlapping, as this helps to avoid neighboring layers from interfering with each other. A useful step size is roughly one tenth of the detector size divided by the magnification used for recording the high-resolution 2D images, which means that every point of the object will be in roughly 10x10 images.

3. Reconstruction

After the CT data set (see Section 2.1) and the high-resolution 2D data set (see Section 2.2) have been recorded, these data sets have to be reconstructed into a 3D voxel data set. This is done by performing an MLEM reconstruction using both the CT images and the high-resolution images as input data. The input data for the MLEM also contains information about the position and angle of the object for each image.

The MLEM algorithm which was modified for taking both data sets as input data is presented in Section 3.4. The MLEM needs both the projection operation, which is described in Section 3.2, and the unfiltered backprojection operation, which is described in Section 3.3. The identifiers used in this section for describing the algorithm are explained in Section 3.1.
3.1 Identifiers

The following identifiers and functions are used for describing the algorithms in this section:

- \( u \) and \( v \) denote the position of a pixel in a 2D image
- \( a \) is an index specifying an image in an image sequence
- \( x, y \) and \( z \) describe the position of a voxel in a volume dataset
- \( n \) is the number of the current iteration
- \( vol_0 \) is the initial result volume
- \( vol_n \) is the resultant volume after iteration \( n \)
- \( \text{normseq}_{\text{CT}}, \text{proj}_{\text{CT}}, \text{proj}^2_{\text{CT}}, \text{normseq}_{\text{high}}, \text{proj}_{\text{high}}, \text{proj}^2_{\text{high}} \) are temporary image sequences
- \( \text{backproj} \) and \( \text{backprojnorm} \) are temporary volume data sets
- \( \text{norm} \) is a normalization volume
- \( \text{input}_{\text{CT}} \) is the image sequence recorded in the first step (see Section 2.1). Each image of the image sequence shows the entire object at a different rotation. \( \text{input}_{\text{CT}}(u, v, a) \) is the attenuation at the pixel \((u, v)\) of image \(a\).
- \( \text{input}_{\text{high}} \) is the image sequence recorded in the second step (see Section 2.2). Each image of the image sequence shows a small part of the object at a high resolution. \( \text{input}_{\text{high}}(u, v, a) \) is the attenuation at the pixel \((u, v)\) of image \(a\).
- \( P_{\text{CT}}(V) \) is a sequence of images generated by the forward projection of the volume \(V\) using the geometries used in the first recording step
- \( P^T_{\text{CT}}(I) \) is volume generated by the unfiltered backprojection of the image sequence \(I\) using the geometries used in the first recording step
- \( P_{\text{high}}(V) \) is a sequence of images generated by the forward projection of the volume \(V\) using the geometries used in the second recording step
- \( P^T_{\text{high}}(I) \) is volume generated by the unfiltered backprojection of the image sequence \(I\) using the geometries used in the second recording step

3.2 Projection

The projection operation is the inverse operation of the reconstruction. It simulates the process happening while acquiring the CT images and creates a set of virtual CT images from a 3D voxel data set. Each image in the output sequence shows the result of a simulated X-ray image for a certain geometry (i.e. for a certain angle, object position and source-detector distance). [3, 4]

The following steps are used to calculate the projection \( \text{proj} = P(vol) \). The algorithm iterates over all images \(a\) in the output image sequence.

\[
a \in \{1, \ldots, \text{numImages}\}
\]
For each output image, it iterates over all pixels \((u, v)\) in the output image.

\[
(u, v) \in \{1, \ldots, \text{numPixelU}\} \times \{1, \ldots, \text{numPixelV}\}
\]  

(2)

For each pixel in each image, using the geometry for the image \(a\), the point \((\text{det}_x, \text{det}_y, \text{det}_z)\) in 3D space of the detector pixel \((u, v)\) is calculated. Then the line integral from the position of the source \((\text{src}_x, \text{src}_y, \text{src}_z)\) to the position of the detector \((\text{det}_x, \text{det}_y, \text{det}_z)\) is calculated using trilinear interpolation and is stored as output for the current pixel.

\[
\text{vec} := (\text{det}_x, \text{det}_y, \text{det}_z) - (\text{src}_x, \text{src}_y, \text{src}_z)
\]  

(3)

\[
dist := |\text{vec}|
\]  

(4)

\[
dir := \frac{\text{vec}}{\text{dist}}
\]  

(5)

\[
proj(u, v, a) := \int_0^{dist} \text{vol} (\text{src} + s \cdot \text{dir}) \, ds
\]  

(6)

### 3.3 Unfiltered backprojection

The unfiltered backprojection is an operation which can be used to create a 3D voxel data set from an image sequence. Using the backprojection as a reconstruction algorithm without a filter will lead to a very blurry image where it is hard to see details, so normally a high-pass filter is applied before the backprojection which will lead to the filtered backprojection. Another use of the unfiltered backprojection is as part of the MLEM. This use is based on the fact that the unfiltered backprojection is the transpose operation to the projection shown in Section 3.2.

The following steps are used to calculate the unfiltered backprojection \(\text{vol} = P(\text{proj})\). First, all voxel in the output data set \(\text{vol}\) are set to 0.

\[
\text{vol}(x, y, z) := 0
\]  

(7)

Next, the algorithm iterates over all images \(a\) in the image sequence.

\[
a \in \{1, \ldots, \text{numImages}\}
\]  

(8)

For each image, it iterates over all voxels \((x, y, z)\) in the output volume.

\[
(x, y, z) \in \{1, \ldots, \text{numVoxelX}\} \times \{1, \ldots, \text{numVoxelY}\} \times \{1, \ldots, \text{numVoxelZ}\}
\]  

(9)

For each pixel in each image, using the geometry for the image \(a\), the point \((u, v)\) on the detector where a line through the source \(\text{src}\) and the point \((x, y, z)\) will intersect the detector plane is calculated. Then the value at \((u, v)\) is added to the current output voxel, using bilinear interpolation, use 0 when outside the input image.

\[
\text{vol}(x, y, z) := \text{vol}(x, y, z) + \text{proj}(u, v, a)
\]  

(10)
3.4 MLEM

The method proposed in this paper uses a modified maximum likelihood expectation maximization (MLEM) algorithm to reconstruct the data. The MLEM is an iterative method, where an initial guess for the volume data is iteratively improved. Iterative solutions have advantages like higher noise resistance and are therefore widely used for techniques like positron emission tomography where the signal-to-noise ratio is very low. The MLEM considers the problem of CT reconstruction to be a system of linear equations which is then solved iteratively.

\[ A \cdot \text{vol} = \text{input} \]  

Unlike the filtered backprojection, the MLEM allows adding additional information like the 2D images acquired in Section 2.2 into the reconstruction process without any problems. The additional images will be considered additional equations for the system of linear equations.

The following steps are performed during a MLEM with resolution enhancement. First, a normalization volume data set norm is calculated as the unfiltered backprojection of a image sequence where all pixels have a value of 1.

\[ \text{norm}_{\text{seq}}(u, v, a) := 1 \]  

\[ \text{norm}_{\text{high}}(u, v, a) := 1 \]  

\[ \text{norm} := P^T_{\text{CT}}(\text{norm}_{\text{seq}}) + P^T_{\text{high}}(\text{norm}_{\text{high}}) \]  

(See Section 3.3)

Then an initial volume vol\(_0\) is chosen, normally with all voxel set to the value 1, and the current iteration number is set to 0.

\[ \text{vol}_0(x, y, z) := 1 \]  

\[ n := 0 \]

Now, for every iteration, a projection of the current volume is computed.

\[ \text{proj}_{\text{CT}} := P_{\text{CT}}(\text{vol}_n) \]  

(See Section 3.2)

\[ \text{proj}_{\text{high}} := P_{\text{high}}(\text{vol}_n) \]  

(See Section 3.2)

Every pixel in the input image sequence input is divided by the corresponding pixel in the image sequence proj.

\[ \text{proj}_{\text{2CT}}(u, v, a) := \frac{\text{input}_{\text{CT}}(u, v, a)}{\text{proj}_{\text{CT}}(u, v, a)} \]  

\[ \text{proj}_{\text{2high}}(u, v, a) := \frac{\text{input}_{\text{high}}(u, v, a)}{\text{proj}_{\text{high}}(u, v, a)} \]

The unfiltered backprojection of proj\(_2\) is then computed.

\[ \text{backproj} := P^T_{\text{CT}}(\text{proj}_{\text{2CT}}) + P^T_{\text{high}}(\text{proj}_{\text{2high}}) \]  

(See Section 3.3)

Every voxel in backproj is divided by the corresponding voxel in the normalization volume

\[ \text{backproj}_{\text{norm}}(x, y, z) := \frac{\text{backproj}(x, y, z)}{\text{norm}(x, y, z)} \]
Each voxel of the output volume of the current iteration is the output voxel of the previous iteration multiplied with the corresponding voxel in $\text{backprojnorm}$.

$$\text{vol}_{n+1}(x, y, z) = \text{vol}_n(x, y, z) \cdot \text{backprojnorm}(x, y, z)$$  \quad (23)

Now the number of the current iteration is increased and, if the maximum number of iterations has not yet been reached, the next iteration is started.

$$n := n + 1$$  \quad (24)

Figure 2: (a) Slice of input data for simulation, (b) Slice of reconstructed data without resolution enhancement, (c) Slice of reconstructed data with resolution enhancement, magnification for high resolution images is 5x the magnification of normal CT.

The upper three rows of boxes show the areas used for evaluating the contrast using the line pair method, the lower row of boxes shows the area used as undisturbed background (on the left), as undisturbed material (on the right), and the area containing the edge used for evaluating the MTF (in the middle).
4. Results

In order to verify the method, it has been applied to a simulated PCB containing structures which can be used for determining the resolution. Slices through the input data and through the reconstructed results with and without resolution enhancement can be seen in Fig. 2. These images were then used to quantitatively evaluate the improvement of the resolution in Section 4.2, using two different methods which were based on [2].

4.1 Images

For creating the test images a PCB with a size of 1 cm by 1 cm was used. One of the metal layers of the PCB contained line pair structures and an edge for determining the MTF. The input data for this layer can be seen in Fig. 2a.

Based on this structure a CT acquisition process (see Section 2.1) and a high-resolution image acquisition process (see Section 2.2) was simulated. The source-detector distance used was 90 cm, the source-object distance was 5 cm for the CT and 1 cm for the high-resolution images. This means that the resolution factor between the CT images and the high-resolution images is 5. The images generated by this simulation were then reconstructed both using a standard MLEM (using only the standard CT images) and using the algorithm presented in Section 3 (using both the standard CT images and the high-resolution images). A slice through the reconstructed image showing the layer containing the line pair and MTF structures can be seen in Fig. 2b for the standard MLEM and in Fig. 2c for data reconstructed with resolution enhancement. In Fig. 2c the edges are sharper and line pair structures are significantly clearer than in Fig. 2b.

4.2 Quantitative Evaluation of Resolution Improvement

In order to get quantitative data regarding the resolution enhancement achieved by the method proposed in this paper, the images in Fig. 2b and Fig. 2c were evaluated using two different methods based on [2].

For the first method, the MTF was calculated by looking at the edge in the middle of the lower row of boxes. For an ideal system, this should be a sharp edge. In real systems, the edge will be blurred because the high-frequency components are reduced. The values on a line through this edge make up the edge-response function (ERF). In order to limit the influence of noise or artifacts several such lines through the edge are taken and the values are averaged. Then the system’s line-spread function (LSF) is calculated as the derivative of the ERF. The MTF is the discrete fourier transform of the LSF. For displaying the MTF it is normalized to 1 for the spatial frequency of 0 lp/mm.

For the second method, the minima $N_A(i)$ and the maxima $N_B(i)$ were measured for each of the line pair structures $i$. Additionally, the gray value of the undisturbed background $N_A$ (in left box in the lower row) and the gray value of the undisturbed material $N_C$ (in right box in the lower row) were measured. Then the line pair contrast factor $R(i)$ for the $i$th line pair structure is calculated as follows:

$$R(i) = \frac{N_B(i) - N_A(i)}{N_C(i) - N_A(i)}$$  \hspace{1cm} (25)

The MTF and line pair contrast with and without resolutions enhancement depending on the spatial frequency can be seen in Fig. 3.

Normally, a MTF of at least 10% is considered to be necessary for further processing of the image. Without resolution enhancement, an MTF of 10% is reached at 5 lp/mm, a line pair contrast of 10% at 6 lp/mm. With resolution enhancement, an MTF of 10% is reached at 30 lp/mm, a line pair contrast of 10% at 28 lp/mm.
Figure 3: MTF / line pair contrast depending on spatial frequency

Figure 4: Spatial resolution (where MTF / contrast of line pairs is at least 10%) depending on increase in magnification for high-resolution images, (a) absolute resolution, (b) relative improvement over reconstruction without resolution enhancement
In order to analyze the improvement of the resolution for different ratios between the CT magnification and the 2D magnification (i.e. different resolution factors), the maximum spatial frequency where the MTF or line pair resolution is still above 10% was evaluated for different source-object distances for the high-resolution 2D images. This data can be seen for the reconstruction with and without resolution enhancement in Fig. 4a. For the case without resolution enhancement, the 2D data is not used and therefore the data is independent of the resolution factor. Fig. 4b shows resolution for the case with resolution enhancement divided by the resolution without resolution enhancement, i.e. the relative improvement in resolution achieved by this method. It can be seen that the improvement is nearly the same as the resolution factor, i.e. the resolution in the reconstructed data is almost as good as the resolution in the high-resolution 2D images.

One limitation of this evaluation is that it does not take into account the effect of the focal spot size on the resolution of the resulting 3D voxel data set. In order to achieve a high resolution, the focal spot used for taking the high-resolution images in Section 2.2 has to be very small. However, this can be achieved because the amount of material which has to be penetrated by the X-rays is very low (because the structure is perpendicular to the source-detector line) and therefore the X-ray current can be chosen low. (The X-ray voltage should be the same as the one used for the CT in Section 2.1 because otherwise the different X-ray spectra might cause artifacts during the reconstruction.)

5. Conclusion

This paper has shown a method to integrate high-resolution 2D images into a low-resolution CT data set during reconstruction. The method uses an iterative reconstruction with MLEM to combine the data acquired using a standard CT and high-resolution 2D images acquired with a significantly lower source-object distance into a high-resolution 3D data set. The method has been tested using simulated data, and an improvement in the resolution of 4.6 as measured using MTF and 4.2 measured using line pairs was achieved for a factor of 5 between the magnification used for acquiring the CT data and the magnification used for acquiring the high-resolution images.

References


