Thick Slices from Tomosynthesis Data Sets: Phantom Study for the Evaluation of Different Algorithms

Felix Diekmann,¹ Henning Meyer,¹ Susanne Diekmann,¹ Sylvie Puong,² Serge Muller,² Ulrich Bick,¹ and Patrik Rogalla¹

Tomosynthesis is a 3-dimensional mammography technique that generates thin slices separated one to the other by typically 1 mm from source data sets. The relatively high image noise in these thin slices raises the value of 1-cm thick slices computed from the set of reconstructed slices for image interpretation. In an initial evaluation, we investigated the potential of different algorithms for generating thick slices from tomosynthesis source data (maximum intensity projection—MIP; average algorithm—AV, and image generation by means of a new algorithm, so-called softMip). The three postprocessing techniques were evaluated using a homogeneous phantom with one textured slab with a total thickness of about 5 cm in which two 0.5-cm-thick slabs contained objects to simulate microcalcifications, spiculated masses, and round masses. The phantom was examined by tomosynthesis (GE Healthcare). Microcalcifications were simulated by inclusion of calcium particles of four different sizes. The slabs containing the inclusions were examined in two different configurations: adjacent to each other and close to the detector and with the two slabs separated by two 1-cm thick breast equivalent material slabs. The reconstructed tomosynthesis slices were postprocessed using MIP, AV, and softMip to generate 1-cm thick slices with a lower noise level. The three postprocessing algorithms were assessed by calculating the resulting contrast versus background for the simulated microcalcifications and contrast-to-noise ratios (CNR) for the other objects. The CNRs of the simulated round and spiculated masses were most favorable for the thick slices generated with the average algorithm, followed by softMip and MIP. Contrast of the simulated microcalcifications was best for MIP, followed by softMip and average projections. Our results suggest that the additional generation of thick slices may improve the visualization of objects in tomosynthesis. This improvement differs from the different algorithms for microcalcifications, spiculated objects, and round masses. SoftMip is a new approach combining features of MIP and average showing image properties in between MIP and AV.

KEY WORDS: 3D Imaging (imaging, 3-dimensional), tomography, x-ray, computed, digital mammography

INTRODUCTION

Many research projects try to improve the outcome in breast imaging—for example with Ultrasound, magnetic resonance imaging (MRI), and digital mammography.^{1–5} One very promising technique for further improvement of breast imaging is Tomosynthesis,⁶ which is a fairly recent technique of mammography and provides 3-dimensional images of the breast with reduced interference from overlaying structures. Initial clinical evaluation suggests that this new technique is a very promising candidate for improving breast cancer diagnosis.^{7–11} Only little attention has been paid to the most suitable presentation and postprocessing of the source data obtained by tomosynthesis so far. While earlier investigators generated the final slices from the original set of about 15 tomosynthesis images using a shift and

¹From the Department of Radiology, Charité-Universitätsmedizin Berlin, Charitéplatz 1, 10117, Berlin, Germany.

²From the GE Healthcare, 283 rue de la Minière, 78530, Buc, France.

Correspondence to: Felix Diekmann, Department of Radiology, Charité-Universitätsmedizin Berlin, Charitéplatz 1, 10117, Berlin, Germany; tel: +49-30-450527245; fax: +49-30-450527945; e-mail: felix.diekmann@charite.de

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add technique,^{6,12} most systems today operate with filtered back projection or linear algebraic algorithms,¹³ which are known from other entities like computed tomography (CT). Another algorithm that can be used is “iterative maximum-likelihood expectation maximization”,¹⁴ which allows relatively fast reconstructions.

With this technique, it is possible to compute thin slices from the source data (e.g., 1-mm slices) and to display these images as a movie using the cine mode. However, these thin slices are degraded by a very high image noise level. One could also think about additional direct reconstruction of thicker slices from tomosynthesis raw data, but this would result in very high additional reconstruction times (in the moment ca. 20 min per reconstruction). It is expected that such high noise levels will especially degrade the visualization of very small structures, such as microcalcifications, and of structures with very low contrast.¹⁵ A similar effect occurred with the advent of multislice CT scanners, which typically first generate thin slices with high noise levels that are then postprocessed to obtain thick slices (e.g., 1-cm slices). Thick slices are typically generated using maximum intensity projection (MIP), not only in CT but also for other imaging modalities (e.g., to obtain a rapid overview in breast MRI). An inherent limitation of MIP is that noise is not reduced as effectively as with other postprocessing techniques (e.g., averaging of individual pixels using the average algorithm [AV]). The question therefore arises whether MIP images are adequate in breast imaging where it is important to identify minute structures such as microcalcifications and low-contrast structures. MIP and AV using maximum values and average values, respectively, are well established but it is conceivable to generate images using more complex functions. In this study, we also tried a new approach we called “softMIP” algorithm, which uses a more complex function for creating thick slices than AV or MIP. In this phantom study, we investigate the two known and the new algorithm for generation of secondary thick slices from tomosynthesis source data sets and compare how the different postprocessing techniques affect the calculated image quality.

MATERIALS AND METHODS

Tomosynthesis of the Phantom

An especially designed x-ray phantom (CIRS, Norfolk, VA, USA) containing objects that simulate microcalcifications, round masses, and spiculated masses was examined by tomosynthesis mammography (GE Healthcare, Buc, France). This system acquires 15 individual tomosynthesis projected views at different gantry angles (from -20 to $+20^\circ$) while the object remains motionless on the detector, which is likewise static. Geometrical magnification was not used. Moreover, no anti-scatter grid was used. The average glandular dose delivered for the acquisition of the 15 projected views is normally about 1.5 times the dose of a single “normal” digital mammogram (depending on the system used for digital mammography and on the thickness/density of the breast). Since tomosynthesis is a 3D technique, it is believed that only one view needs to be acquired.¹⁶ In our example, a comparable breast would have been exposed to an average glandular dose (AGD) of about 1.5 mGy using a modern digital mammography system with automatic parameter selection, compared to 2 mGy calculated AGD for tomosynthesis images of our phantom (1.33 times more dose for tomosynthesis compared to a “normal” digital mammography).

The especially designed phantom used in this study has a total height of 5 cm (size xy-direction is 10×10 cm) and is composed of six slabs: three slabs of 1-cm-thick breast equivalent material, two slabs of 0.5-cm-thick breast equivalent material containing different objects of interest simulating lesions (slabs A and B) and a 1-cm thick slab of swirl material placed on top of the phantom to simulate breast textured tissue. Figure 1 shows the two different configurations in which the phantom was examined by tomosynthesis. The objects of interest were microcalcifications of different sizes and round and spiculated masses of variable sizes and thickness (see Fig. 2). In configuration I, slabs A and B containing the objects were separated by two breast equivalent material slabs. Slab A has been placed close to the textured material to assess the impact of glandular tissues to the visibility of lesions in reconstructed slices. In configuration II,

Configuration I: **Configuration II**

Fig 1. Scheme of the two different configurations of our phantom for tomosynthesis.

slabs A and B were adjacent to each other. This configuration has been chosen to have a first idea of the capability of the postprocessing to help the display of volumetric information of several “near-by”—lesions present in several reconstructed slices.

Software Processing of the Phantom Images

An algorithm called SART (Simultaneous Algebraic Reconstruction Technique)¹³ was used to calculate thin slices separated one from the other by 1 mm from the 15 tomosynthesis projected views. The resulting thin slices were then post-processed to obtain 1-cm thick slices by using three different algorithms. The first algorithm, maximum intensity projection (MIP), generates a thick slice from a set of thin slices in which the resulting pixels represent the brightest voxels of each stack of slices (Fig. 3). On the other hand, in averaged projections the pixels in the resulting image are the arithmetic means of the voxel stacks. A third algorithm used in this study computes the values of the resulting pixels as the weighted

average of the sorted stack of corresponding voxels. The voxels are weighted accordingly to a weighting function, which characterizes the images. In detail one can say that similar to MIP and AVG, in softMip 1 pixel is calculated from the pixel values along a corresponding viewing ray. These values constitute the profile P of pixel P . Length l of P depends on the slice thickness s and projection geometry—in parallel projection $l=s$ and in perspective projection $l>s$. What is crucial for this algorithm is to incrementally order P , resulting in P_s with $P_s(0)=\min(P)$ and $P_s(l)=\max(P)$. Pixel P is then calculated as the normalized, weighted integral of the ordered profile:

$$P = \frac{1}{\int_0^1 f_w(x) dx} \int_0^1 f_w\left(\frac{x}{l}\right) \cdot P_s \cdot x dx$$

where $f_w(x)$ with $0 \leq x \leq 1$ is the weighting function of softMip, which strongly determines the result of softMip f^w . For example, $f_w^{MIP}(x) = \begin{cases} 1; & \text{if } x > 0.999 \\ 0; & \text{else} \end{cases}$ will generate a MIP and $f_w^{AVG}(x) = 1$ an Average Image. A image with noise suppression and MIP features like we used for this study is generated by $f_w(x)=x^4$. This function was taken as a result of experiences from

Slab A:

Ø	µcal 280- 300	SM 1.45 5/16	Ø
RM 3.2 7/32	SM 2.05 7/32	µcal 250- 280	Ø
µcal 180- 200	RM 4.0 5/16	Ø	Ø
SM 3.2 7/32	Ø	Ø	µcal 125- 140

Slab B:

RM 1.45 3/8	µcal 180- 200	Ø	SM 1.45 3/16
Ø	Ø	µcal 250- 280	RM 2.05 5/16
RM 3.2 3/8	µcal 280- 300	Ø	SM 3.2 5/16
µcal 300- 355	Ø	RM 4.0 3/8	SM 4.0 3/16

Fig 2. Diagram of the phantom used and the two configurations of the slabs with the included objects (diameters microcalcification: µcal; SM: spiculated masses; RM: round masses).

detection of calcifications in noisy thin-slice CT images.¹⁷

Evaluation of Phantom Images

The thick slices obtained with the three algorithms, MIP, average, and softMip, were evaluated for image quality. This was done by calculating the contrast of microcalcifications by measuring the

maximum grayscale values of six microcalcifications and relating these to the grayscale value of background according to the formula:

$$C = \frac{(\overline{P_1} - \overline{P_2})}{(\overline{P_1} + \overline{P_2})}$$

where C is the calculated contrast, P_1 represents the pixel values of the calcification, and P_2 repre-

Fig 3. MIP images are computed as the maximum value of a voxel stack, whereas average computes the average of all corresponding values of a pixel. Similar to calculating Average softMip calculates the resulting pixel value through a (more complicated) function.

Fig 4. Examples of original thin slices and 1-cm slices generated by MIP, Average (AV), and softMip. Top: 200- μ m microcalcifications, bottom: round mass.

sents the pixel values of the background. Six contrast values calculated for different calcifications of a calcification group were then used to derive a mean contrast (only the highest pixel value from each microcalcification was used. Calculation of contrast-to-noise ratio [CNR] [see below] was not done for microcalcifications, because it is unreliable to calculate the noise of microcalcifications—too few pixels would contribute to this calculation). For the phantom configurations I and II, the mean contrast values from the six microcalcifications in thin reconstructed slices and the three thick slices generated by the three postprocessing algorithms were plotted against each other for comparison. For the other two types of objects in the phantom, round masses (RM) and spiculated masses (SM), contrast-to-noise ratios were calculated for each of the three postprocessing algorithms. CNR was calculated as the ratio of difference between the mean pixel values in the object (P_1) and in the background (P_2), and the square root of the sum of their variances using the formula:

$$CNR = \frac{(\bar{P}_1 - \bar{P}_2)}{\sqrt{\sigma_{\bar{P}_1}^2 + \sigma_{\bar{P}_2}^2}}$$

A mean value from three clearly visible and measurable spicula of the spiculated masses was used for SM and a large region of interest (ROI)

from the lesion for RM. ROIs placed in the background of the respective lesions were used for comparison (minimum size of a ROI was 100 pixels).

RESULTS

The MIP Algorithm was the best algorithm for visualization of microcalcifications (see Figs. 4 and 5) in our study. Average Algorithm performs best in CNR of round masses and spiculated masses (see Figs. 6 and 7). Results of the third algorithm (softMip) are in between Average and MIP for both microcalcifications and simulated masses. This tendency can be shown for all settings (configuration I and II).

For “critical imaging situations” like for the smallest calcifications (which have a lower contrast than the other high-contrast objects), the contrast in softMip images is nearer to the contrast in the MIP images (Figs. 4 and 5) compared to “non critical imaging situations”. On the other hand one has to realize that contrast values in this “critical imaging situations” are still very much below the MIP images. This tendency for “critical imaging situations” is also observed for the visualization of simulated masses (see Fig. 6), where the image quality of softMip is nearer to the quality of Average images in very small objects compared to larger objects.

Fig 5. Results of contrast measurements of microcalcifications in Configuration I—contrast versus diameter in micrometer.

Fig 6. Results of contrast measurements of microcalcifications in Configuration II—contrast versus diameter.

DISCUSSION

When digital mammography was introduced at the beginning of the millennium, much of the discussion focused on hardware, less attention was paid to software. However, it has been shown that the software is just as important as the hardware parameters for the visualization of tumors.^{18,19} The image processing algorithms investigated in this phantom study have advantages and disadvantages. Advantage of MIP algorithm is the high contrast in the resulting images. Disadvantage of MIP is the high noise level in the images. Advantage of Average images is the low noise level in the images, but on the other hand there is very low contrast in these images. SoftMip shows image qualities in between MIP and Average.

Examples of thick slices generated by MIP, Average, and SoftMip are presented in Figure 8. In these examples, one can see that contrast for high-contrast objects such as microcalcifications is best on the MIP thick slice, whereas the contrast for AV is poorest. SoftMip thick slice is only slightly below the one of MIP regarding the contrast. The high noise level of MIP images degrades image quality especially at object boundaries. Overall, the

results show extremely low noise and low contrast for AV images, an intermediate noise level and acceptable contrast for the softMip algorithm and relatively high noise with very good contrast for MIP (see Fig. 7: average overall sizes of RM and SM). As a result of the poor contrast in AV images, small microcalcifications may be missed or very difficult to see (just as in the original thin slices). As a compromise between the two extremes, SoftMip projection has the potential to be optimized further for specific applications. Promising is the fact that SoftMip is nearer to the image quality of MIP for microcalcifications and the image quality of Average for masses especially in “critical situations” like very tiny microcalcifications or very tiny low contrast objects (masses) compared to “noncritical situations”.

For our methods of noise reduction shown in this study pixel values of “neighbored” pixels were not taken into account. One could think about more sophisticated methods for noise reduction that take into account all the pixel values of many “neighbored” pixels in future.

Based on our phantom results, one can attempt to draw conclusions as to which of the projections will be most beneficial for specific applications in

Fig 7. Example of contrast-to-noise ratios of round masses.

Fig 8. Average contrast-to-noise ratios of round masses (RM) and spiculated masses (SM) in Configuration I and Configuration II.

clinical practice. The hardware and software demands are especially high in mammography. This is why the different thick slice algorithms investigated in this paper may be especially helpful for improving the visualization of low-contrast objects and very small structures. On the other hand, it is known from multislice CT that the thin slices often contain additional information (e.g., to demonstrate or exclude partial volume effects). It is therefore possible that both thin and thick slices will be used for interpreting tomosynthesis data in the future.

Generation of thick slices maybe also a point for decreasing the storage capacity needed for tomosynthesis (approx. 50×8.5 MB for reconstruction of thin slices for 5-cm breast thickness and 8.5 MB per slice). If one would only store the thick slices and raw data, the amount of data would be decreased without losing the possibility of instant look at processed images.

We were able to show that in principle generation of thick slices may increase the visibility of objects in tomosynthesis in different ways. SoftMip is a new approach combining features of MIP and average showing image properties in between MIP and AV. Although our calculated results are promising, further clinical studies and perception studies will have to

show which algorithms are best suited for the visualization of specific pathologies by tomosynthesis.

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