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Workflow improvements for digital breast tomosynthesis: computerized generation of enhanced synthetic images

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ABSTRACT

In a typical 2D mammography workflow scenario, a computer-aided detection (CAD) algorithm is used as a second reader producing marks for a radiologist to review. In the case of 3D digital breast tomosynthesis (DBT), the display of CAD detections at multiple reconstruction heights would lead to an increased image browsing and interpretation time. We propose an alternative approach in which an algorithm automatically identifies suspicious regions of interest from 3D reconstructed DBT slices and then merges the findings with the corresponding 2D synthetic projection image which is then reviewed. The resultant enhanced synthetic 2D image combines the benefits of a familiar 2D breast view with superior appearance of suspicious locations from 3D slices. Moreover, clicking on 2D suspicious locations brings up the display of the corresponding 3D regions in a DBT volume allowing navigation between 2D and 3D images. We explored the use of these enhanced synthetic images in a concurrent read paradigm by conducting a study with 5 readers and 30 breast exams. We observed that the introduction of the enhanced synthetic view reduced radiologist’s average interpretation time by 5.4%, increased sensitivity by 6.7% and increased specificity by 15.6%.

Keywords: Computer-aided detection (CAD), digital breast tomosynthesis (DBT), digital mammography, synthetic images

1. INTRODUCTION

Recently there has been a growth in utilization of digital breast tomosynthesis (DBT). This is a relatively new imaging modality in which systems image a breast by moving an X-ray source and exposing the breast to radiation from multiple angles, thus acquiring high resolution, planar digital projections. Projection data is then processed to create the whole 3D image of the breast using one of the available reconstruction methods. These images help radiologists to see important mammographic structures such as masses, architectural distortions and microcalcifications at various reconstruction heights. 3D DBT images improve the visibility of the findings that may otherwise be obscured by overlapping tissue on a typical 2D mammography image. Several studies showed an increased value of adding DBT to a conventional 2D mammography by reporting improved sensitivity and/or specificity of cancer detection.

However, there is a significant increase in interpretation time of DBT relative to 2D mammography as reported by several clinical studies. This is expected considering that a reader has to process another spatial dimension of visual information. Traditional computer-aided detection (CAD) which is used as a second reader is unlikely to lessen the problem of the interpretation time since the browsing of 3D detection marks will slow down a radiologist even more. As a possible solution, it has been proposed that the generation of a synthetic 2D projection from a DBT volume can help radiologist in the image interpretation workflow. One can create maximum intensity projections (MIP) directly or modulate the resultant projection by sharpness or conspicuity of the structures of interest. Alternatively one can run automated detection algorithm and drive the creation of synthetic image using the detection marks. Among the advantages of synthetic 2D projections is that they are generated without extra dose and may potentially replace traditional 2D mammography images often acquired concurrently with the DBT images.

In this work we propose to use detection algorithm to perform 2D synthetic image enhancement. Here instead of displaying the 3D CAD marks directly on 3D volume, we copy corresponding 2D regions of interest (ROI) from...
locations detected in 3D DBT and insert them into a 2D projection image. We explore the case where the 2D projection image is General Electric’s “V-Preview” synthetically generated by a MIP-like algorithm, however one may use different means of creating a synthetic image as well as using conventional 2D digital mammography image, if it was acquired simultaneously with the DBT without shift in position and compression.

The above ROI enhancement approach has advantages over presenting detection marks on a 3D image from both reader and algorithm perspectives. The advantage for a reader is that the resultant enhanced synthetic image combines the familiar look of 2D mammography with the level of detail of individual DBT slices. Radiologists that are used to interpreting 2D digital and film mammography may have a shorter learning period when transitioning to interpretation of DBT. An advantage of this scheme from the detection algorithm perspective is that it need not be optimized for high sensitivity and high specificity. On one hand, since many of the lesions are already visible on a 2D image, such an enhancement scheme may tolerate few detection misses. On the other hand, enhancing obvious non-cancers should not affect the performance of the reader, since it will be easy for them to dismiss such ROIs on the modified image. Within this paradigm, even an algorithm with suboptimal detection performance may result in a boost of a reader’s performance. Finally, given the established geometry mapping between a DBT volume and corresponding synthetic image, the reader may quickly navigate back and forth between the images just by clicking on suspicious ROIs.

2. METHOD

The scheme for generation of an enhanced synthetic 2D image consists of several stages and is shown in Figure 1. In this paper we particularly focus on the steps of applying the detection algorithm and ROI merging. Methods for 3D reconstruction and creation of 2D synthetic images, although important for the enhancement, are beyond the scope of this work.

2.1 Detection

Our detection pipeline is based on the algorithm originally designed to run on 2D mammography images and modified to process reconstructed DBT volumes on a slice-by-slice basis. The algorithm consisted of a high sensitivity multiscale candidate generator targeting two soft tissue density abnormality types: masses and architectural distortions. Each candidate was defined by its coordinates within a reconstructed DBT volume or a 2D mammography image and its approximate size. A simple algorithm based on conditional random field inference was used to segment the mass candidates. The candidates were then passed to a feature extractor which computed over 300 carefully tuned features including multiscale contrast, histogram, gradient, texture, shape and topology descriptors.

The final classifier was trained on a combination of multi-vendor 2D mammography and 3D DBT data. Because of the limited availability of malignancy-proven cancer cases in our database, we used all suspicious findings that had been annotated by a radiologist, including cancers and suspicious lesions with non-negative BI-RADS ratings. Each annotation contained a hand-drawn contour of the lesion on a reconstructed slice with the sharpest lesion appearance. The contour was supplemented with top and bottom delimiting points indicating the visible extent of the lesion along z-axis. We assembled a training set containing 1864 suspicious soft tissue
density lesions from 2D mammography and 339 lesions from DBT. Approximately a third of these lesions were proven to be malignant. The 2D mammography subset contained digitized film, CR and DR mammography images from various vendors. The DBT subset contained exclusively GE SenoClaire 3D DBT volumes.

We selected an ensemble of boosted decision trees as the classifier as it had been internally demonstrated to achieve highest classification performance and robust vendor independence among all explored classification methods. In the postprocessing step, we eliminated majority of overlapping detections leaving only the ones with the locally maximal classification score. It is possible that some of the detections would still remain clustered together with little or no overlap. The sketch of the detection approach is shown in Figure 2.

2.2 ROI reprojection

Once suspicious findings are identified from the 3D DBT volume, the 2D ROIs are extracted from corresponding planar reconstructions. The size and location of the ROIs are determined by the estimates computed by the candidate generator. Because of the scale difference between the reconstructed DBT slices and synthetic 2D projection, the extracted ROIs are reprojected to the synthetic image plane using projective transform defined by the geometry of tomosynthesis acquisition device.

2.3 ROI merging

Since the image contents of the synthetic view and reconstructed slices are different, one needs to seamlessly blend the ROIs to preserve the overall look of the original image. We performed the merging with the Poisson image blending algorithm\textsuperscript{13} for low-frequency bands of both the synthetic and the ROI images as depicted in Figure 3. Performing blending for low-frequency image bands allows us to achieve two goals. First, due to the different acquisition nature of synthetic 2D and 3D DBT images, high-frequency bands are drastically different and contain different noise patterns. Merging an ROI "as is" would result in visible high-frequency artifacts that would immediately reveal image manipulation. Low-frequency components, in contrast, do not exhibit such differences and can be manipulated without the reader noticing. Second, most microcalcifications should belong to a high-frequency band of the image and therefore would not be affected by low-frequency image manipulation, thus allowing us to focus only on soft tissue densities for which DBT provides superior visual quality. Low-frequency extraction was approximated by convolving both synthetic 2D image and reprojected 2D ROI with the 2D Gaussian kernel of scale in the order of the detector element size.

The blending is formulated as a minimization problem by computing the function whose gradient is the closest to some prescribed vector field (called "guidance vector field") under given boundary conditions. For
Figure 4. Guided interpolation notation. $\vec{v}$ denotes the guidance vector field, which in this case is the gradient of a function inside the original ROI. $f^*$ denotes the known image values outside, and $f$ denotes the unknown image values inside region $\Omega$.

Our merging problem, the guidance vector field $\vec{v}$ is computed from the original ROI region $\Omega$ and the boundary condition forces the smoothness of image inside $f$ and outside $f^*$ intensities of the ROI as as shown in Figure 4. Thus, the optimal blended region inside the ROI $f$ is obtained by minimizing the gradient field differences:

$$f = \arg \min_f \int_{(x,y) \in \Omega} \left| \nabla f(x, y) - \vec{v}(x, y) \right|^2 \, dx \, dy \quad \text{with} \quad f|_{\partial \Omega} = f^*|_{\partial \Omega},$$

where $\nabla = \left[ \frac{\partial}{\partial x}, \frac{\partial}{\partial y} \right]$ is the gradient operator. This equation corresponds to the Poisson’s equation with Dirichlet boundary conditions:

$$\Delta f = \text{div} \, \vec{v} \quad \text{over} \quad \Omega \quad \text{with} \quad f|_{\partial \Omega} = f^*|_{\partial \Omega},$$

where $\Delta = \left[ \frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2} \right]$ is the Laplace operator and $\text{div} \, \vec{v} = \nabla \cdot \vec{v} = \frac{\partial \vec{v}}{\partial x} + \frac{\partial \vec{v}}{\partial y}$ is the divergence of $\vec{v}$.

To illustrate the effect of the blending in the merging procedure let us consider an example where original synthetic 2D image lacks details in appearance of two suspicious lesions is shown in Figure 5(a). Reconstructed DBT slices offer superior visibility of the lesions as can be seen in Figures 5(b) and 5(c). After reprojection of the ROIs from DBT slices to the synthetic view we may observe discontinuities shown in Figure 6(b). However, after applying the Poisson blending these discontinuities disappear making appearance of the lesions more natural as illustrated in Figure 6(c). The final blended image is presented to a reader for the evaluation.

Based on earlier feedback from clinicians, we configured our algorithm to operate at 5 detection marks per image. Given that too many merged ROIs may overcrowd the image, we believe that this is a fair tradeoff between the detection sensitivity and the clarity of the image.

### 3. EXPERIMENT

We used a Multi-Reader, Multi-Case (MRMC) study in which 5 radiologists were to assess 30 2D full-field digital mammography (FFDM) and DBT exams (GE SenoClaire 3D) from women presenting for bilateral screening or diagnostic tomosynthesis exams. The FFDM and DBT exams were assessed with and without the 2D enhanced synthetic images for Concurrent Read Software without a cross-over design and without a washout period so the readings could be completed in one reading session. The 30 cases were randomly split into 2 sets of 15 cases (Sets A and B) matched as closely as possible based on case type and mammographic appearance of the lesions in malignant and benign cases. Each set had 6 cases with malignant findings, 6 cases with benign findings and 3 cases with no findings. The 6 malignant and 6 benign cases in each set consisted of 5 cases with soft tissue density findings (masses, architectural distortions or asymmetries) and 1 case with calcifications. The Set A or B cases were randomly allocated to each radiologist for assessment with or without CAD enhanced images. If the radiologist assessed Set A cases with CAD then he or she assessed Set B cases without CAD and vice versa. The reading order within each case set was also randomized for each reader. Thus, each case was read by each radiologist either with or without CAD enhancement. For the CAD part of the study, the image display workstation was set up such that the readers can navigate between synthetic image and DBT volume back and forth just by clicking on ROIs that are CAD enhanced.

In addition to evaluating performance of the readers, we measured standalone ROI-based CAD sensitivity on a larger dataset of 115 malignant soft tissue densities. We set up the operating point at 5 marks per DBT volume as explained in the method section.
Figure 5. Original synthetic 2D image (a) lacks appearance details of the spiculated masses that are better displayed at respective DBT slices, where ROIs are detected (b) and (c). White arrows point to exact ROI locations at the respective slices.

Figure 6. Creation of enhanced synthetic image involves reprojecting automatically identified ROIs to the synthetic image and blending them with the rest of the image.

4. RESULTS AND DISCUSSION:
The study demonstrated that the interpretation of the studies with of CAD enhanced synthetic view resulted in reduction of the average reading time from 67.8 to 62.3 seconds (actual difference 5.4%), increased case sensitivity
from 0.733 to 0.800 (actual difference 6.7%) and specificity from 0.333 to 0.489 (actual difference 15.6%).

The mean standalone ROI-based sensitivity of our CAD in detecting malignant soft tissue densities was 0.852 ± 0.065 at 5 marks per image. The CAD is not specific, as it consistently outputs 5 detection marks per every DBT volume. However, the CAD enhances many suspicious ROIs that radiologist may or may not act upon. As long as the visibility of the lesions remains high, the final specificity would be controlled by a radiologist, giving them more flexibility and decision power.

5. CONCLUSION

We presented a new way of applying CAD to identify suspicious regions of interest from 3D reconstructed tomosynthesis slices followed by merging them with a 2D synthetic image. Our study demonstrated that the resultant enhanced synthetic image may positively influence the radiologist’s workflow by reducing reading time and increasing detection performance.

REFERENCES