A mathematical model platform for optimizing a multiprojection breast imaging system

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(Received 19 September 2007; revised 1 January 2008; accepted for publication 29 January 2008; published 12 March 2008)

Multiprojection imaging is a technique in which a plurality of digital radiographic images of the same patient are acquired within a short interval of time from slightly different angles. Information from each image is combined to determine the final diagnosis. Projection data are either reconstructed into slices as in the case of tomosynthesis or analyzed directly as in the case of multiprojection correlation imaging technique, thereby avoiding reconstruction artifacts. In this study, the authors investigated the optimum geometry of acquisitions of a multiprojection breast correlation imaging system in terms of the number of projections and their total angular span that yield maximum performance in a task that models clinical decision. Twenty-five angular projections of each breast from 82 human subjects in our breast tomosynthesis database were each supplemented with a simulated 3 mm mass. An approach based on Laguerre–Gauss channelized Hotelling observer was developed to assess the detectability of the mass in terms of receiver operating characteristic (ROC) curves. Two methodologies were developed to integrate results from individual projections into one combined ROC curve as the overall figure of merit. To optimize the acquisition geometry, different components of acquisitions were changed to investigate which one of the many possible configurations maximized the area under the combined ROC curve. Optimization was investigated under two acquisition dose conditions corresponding to a fixed total dose delivered to the patient and a variable dose condition, based on the number of projections used. In either case, the detectability was dependent on the number of projections used, the total angular span of those projections, and the acquisition dose level. In the first case, the detectability approximately followed a bell curve as a function of the number of projections with the maximum between 8 and 16 projections spanning angular arcs of about 23° – 45° , respectively. In the second case, the detectability increased with the number of projections approaching an asymptote at 11–17 projections for an angular span of about 45° . These results indicate the inherent information content of the multiprojection image data reflecting the relative role of quantum and anatomical noise in multiprojection breast imaging. The optimization scheme presented here may be applied to any multiprojection imaging modalities and may be extended by including reconstruction in the case of digital breast tomosynthesis and breast computed tomography. © 2008 American Association of Physicists in Medicine. [DOI: [10.1118/1.2885367](https://doi.org/10.1118/1.2885367)]

Key words: optimization, acquisition parameters, ROC, AUC, Hotelling observer, LG CHO, multiprojection imaging, digital breast tomosynthesis, decision fusion

I. INTRODUCTION

Diagnostic radiology is increasingly embracing modalities that acquire multiple images of the same patient. The multi-

image scheme alleviates the main shortcoming in standard projection imaging techniques: the overlap of anatomical structures (i.e., anatomical noise) that can partially or completely hide a pathology of interest.^{1,2} This is done by har-

nessing the geometrical and statistical dependences between the multiple images available in a multiprojection system. One particular multiprojection acquisition modality, digital breast tomosynthesis, has indeed been shown to provide improved diagnostic performance as compared to the standard projection procedures.³ However, the tomosynthesis technique is prone to reconstruction artifacts,^{4,5} which might reduce the efficiency of tomosynthesis reading, even leading to higher false positive findings.⁶ Therefore, there would be an advantage in using an imaging technique that could fuse information from multiple images, similar to tomosynthesis, but without the confounding effects of the reconstruction.

Toward that end, multiprojection correlation imaging (CI) was recently proposed as an adjunct technique to standard mammography or tomosynthesis.^{7,8} This technique uses the unreconstructed angular projections acquired using an approach similar to tomosynthesis. The projection images are similar to standard mammograms, except that each image is acquired with a lower dose level than that in standard full field digital mammography. The information from the multiplicity of angular projections acquired is then combined to identify potential lesions. Practically, this combination can take different forms including scrolling the images manually or in cine mode, stereoscopic display of projections images, or computer-aided analysis of the multiple images. Thus, CI aims to augment the advantages of standard projection techniques with the proven benefits of multiprojection scheme, without the reconstruction artifacts that otherwise limit tomosynthesis, to deliver an improved diagnostic performance.^{9–11}

While CI has notable potentials, in developing multiprojection CI, an important consideration is its data acquisition scheme. Multiple aspects of data acquisition can influence the performance of CI. Ideally, the data acquisition scheme should avoid patient motion, reduce patient discomfort, and maintain a total dose not exceeding that delivered in a standard projection technique. Beyond these, however, the diagnostic outcome of a multiprojection system is strongly dependent on the geometry of acquisition: the number of angular acquisitions and the total angular span of those acquisitions as geometry of acquisitions play a pivotal role in establishing correlation information in CI. It is therefore important that image acquisitions parameters be optimized to maximize the diagnostic information of such a system.

In this study, we investigated the optimal number and range of angular projections of a multiprojection breast CI system based on maximizing performance in a task that models clinical practice. The performance was measured in terms of detectability of an embedded simulated mass using a mathematical observer model.^{12–16} As a key element of the study, three techniques were developed to combine the information content from individual angular projections to derive a combined receiver operating characteristic (ROC) curve that indicates the overall detectability of the mass. To optimize the geometry of acquisitions, the acquisition parameters were systematically changed to determine which one of the combination of parameters would maximize the area under the combined ROC. Optimization was investigated under

FIG. 1. The prototype multiprojection breast imaging instrument.

two key dose considerations corresponding to a fixed total dose delivered to the patient and a variable dose condition in which the total patient dose increases with the number of projections acquired.

II. MATERIALS AND METHODS

II.A. Image database

The study employed a database of images of the left and right breasts of 82 subjects originally acquired as a part of our tomosynthesis clinical trial at Duke. Images were acquired about the CC or MLO orientation from 25 different but fixed angular positions by a prototype clinical multiprojection system, a modified Siemens' Mammomat Novation^{TOMO} (Fig. 1). The system used a selenium-based, flat-panel, digital mammography detector with an array size of 2816×3584 and a pixel pitch of $85 \mu\text{m}$. The system used a tungsten target, a $50 \mu\text{m}$ rhodium filter, a source to image distance of 65.3 cm, and an isocentric gantry pivoting the x-ray tube about a point located 6 cm above the detector. The projection angles of the 25 images were varied within 45° angular range about the central orientation (CC or MLO) in steps of approximately 2° . The tube voltage ranged between 28 and 30 kVp to obtain consistent image contrast across different compressed breast thicknesses in the 3–8 cm range in our clinical trial. The total dose delivered to the patient from 25 angular acquisitions was equivalent to that delivered in a standard two-view mammographic screening procedure, with each angular projection at a dose level, D_θ , equal to $1/25$ th of the total clinical dose. All images were judged by a dedicated breast-imaging radiologist to be free from suspicious lesions.

492 regions-of-interest per projection angle (ROIs) ($2 \text{ breasts} \times 82 \text{ patients} \times 3 \text{ ROIs/projection}$) of size 512×512 ($43.5 \times 43.5 \text{ mm}^2$) were extracted from the database. The displacement of the ROIs on the detector across the different angular projections was taken into account so that the ROIs from the same patient represented the same general volume of the breast. There was a slight difference in the breast volume being sampled as a function of the projection angle. However, this difference was found to be inconse-

quential since changing the ROI size was found to have a minimal effect on the overall performance of the observer model. From the pool of extracted ROIs, 264 were used for training the observer model, while the remaining 228 ROIs were used for testing.

II.B. Three-dimensional lesion simulation

A simulated mammographic lesion, 3 mm in diameter, was digitally inserted into the ROIs generated above. The size of the lesion enabled a difficult but clinically relevant detection task. The lesion was simulated in three dimensions (3D). To do so, first a two-dimensional projection profile based on a previously published model of lung and breast lesions was generated.^{15,17,18} Starting from this profile, the surface of the central slice of the lesion was reconstructed using inverse radon transform, assuming that the lesion is isotropic and the different angular projections along the plane of the central slice would yield the same profile across the central slice. The central slice was then rotated about its diameter to complete the simulation of a three-dimensional (3D) lesion.

The 3D lesion was projected into the 25 angular projections assuming that the lesion was embedded at the center of the ROI volume (2–8 cm in compressed thickness) at a distance of 3 cm from the detector. The x and y coordinates of the projected lesion on the image plane were computed as

$$x_i = \frac{x(D + L \cos \phi) - zL \sin \phi}{D + L \cos \phi - z},$$

$$y_i = \frac{y(D + L \cos \phi)}{D + L \cos \phi - z}, \quad (1)$$

where (x, y, z) are the positional coordinates of any point on the lesion, (x_i, y_i) are the corresponding coordinates in the image plane, ϕ is the projection angle, and L and D are the distances of the pivotal point from the source and the detector, respectively. These equations were derived based on the trajectory of the acquisition system and are consistent with prior work.^{19,20} Figure 2 shows projection of the 3D lesion on the detector from three different tube angular orientations of $+22^\circ$, 0° , and -22° relative to the CC orientation.

The ratio of the contrast of the lesion to its diameter (set to 3 mm) was determined from published contrast/lesion thickness ratios based on the acquisition kVp, target/filtration combination, detector type, compressed breast thickness, and breast composition.¹⁷ Since increased glandularity decreases lesion contrast, a 75/25% glandular/adipose breast composition was used to represent a difficult but clinically relevant detection task. The contrast ratio was further modified to take scattering into account. Toward that end, the scatter-to-primary ratio for the central projection was computed based on an earlier study.¹⁷ This ratio was used as a representative value for all the projections, not reflecting slight variations in the scatter-to-primary ratio with angular projections.²¹ Although consistent with the value reported in an earlier study, the variation of scatter to primary ratio with was ignored. The lesions were then added to the ROI in the log space such

FIG. 2. Example images of projections of 3D model of a 3 mm simulated lesion assumed to be 3 cm above the detector. These lesions were embedded on tomographic projections to emulate the lesion-present mammographic background. (a), (b), and (c) show the projections with the tube orientation at $+22^\circ$, 0° , and -22° , respectively, relative to the CC orientation.

that the contrast of the lesion over the background was independent of the breast composition or thickness. The lesions were embedded onto the different ROIs to generate 492 signal-present ROIs for each angular projection. Figure 3 shows example images of ROIs with the embedded simulated lesion.

II.C. Noise simulation

Following extraction of ROIs, a noise modification routine was used to add radiographic noise to each of the ROIs to create images with a noise appearance similar to that caused by reduction in radiation dose from D_θ . Noise equivalent quanta of a particular dose level was simulated using an algorithm reported earlier.²² The algorithm accounted for the quantum noise variance, the detector transfer properties and its noise characteristics, and the impact of varying attenuation of breast structures. By changing the noise magnitude, 24 dose-reduction levels, corresponding to $D_\theta/20$ – $D_\theta/25$, were simulated. These with the original clinically acquired images at D_θ resulted in images with 25 contiguously decreasing dose levels. Figure 3 shows examples of ROIs with different dose levels. While Fig. 3(a) shows the original clinically acquired image, Figs. 3(b) and 3(c) show the same ROI with added simulated noise corresponding to reduced dose level of $D_\theta/2$ and $D_\theta/25$, respectively.

II.D. Mathematical observer model

Linear mathematical observer models, such as Hotelling observers, have been shown to predict human observer performance in clinically relevant visual tasks such as the detection of lesions in real anatomic backgrounds.^{15,23–25} This study employed a variant of the Hotelling observer, namely the Laguerre–Gauss channelized Hotelling observer (LG CHO). LG CHO uses linear features that are product of Laguerre polynomials and Gaussians functions to reduce the dimensionality of the Hotelling observer, thus making the implementation mathematically tractable. The variance of the Gaussian function is related to the signal radius and is determined iteratively to maximize the area under the ROC curves (AUC).¹⁵ A variance of 10 was used in this study. The present implementation further used a total of ten channels which is more than sufficient for characterizing isotropic signals used in our study (as shown in Fig. 2).²⁶

The covariance matrix of the LG CHO was trained with signal-absent ROIs. Using a methodology previously published,¹⁶ a set of signal-absent and signal-present decision variables were determined for each angular projection. Nonparametric ROC curves were then derived by simple thresholding on the probability density function (pdf) of the decision variables. While testing using the LG CHO, signal in each of the ROIs was analyzed with the signal-known exactly methodology, assuming that the lesions embedded in different ROIs within the same angular projection have approximately the same shape. The results were characterized in terms of the ROC for each of the 25 angular projections with the area under the mean ROC curve subsequently determined using the trapezoidal rule.

II.E. ROC fusion

Twenty-five ROCs obtained from the 25 angular projections are indicative of the performance of an observer as it analyzes each of those projections separately. Since the final clinical decision is based on a collective decision made from

FIG. 3. Example projection images of ROIs with 3 mm simulated lesions embedded at the center. (a) shows the ROI of a clinically acquired projection with dose level, D_θ , equal to $1/25$ th that of standard mammographic screening. (b) and (c) show the same ROI with noise corresponding to $1/2$ and $1/25$ th fraction of D_θ .

detectability cues gathered from each angular projection, it is essential to fuse the 25 ROCs into one final index of performance. Toward that end, two fusion methods were used and their performance compared to the average of the 25 ROCs.

In the first method, a weighted average of the signal-present decision variables from the 25 angular projections was computed to determine a final set of decision variables from which the combined ROC was derived. The weight assigned to the decision variable of an angular projection, θ , was based on the difference of detectability index between the value at the angular projection under consideration, d'_θ , and that at the central (CC or MLO) projection, d'_{CC} , and the absolute value of the angular separation between the two ($\theta - CC$), as $w_\theta = (d'_\theta - d'_{CC}) / (|\theta - CC|)$. The underlying hypothesis for this technique was that the overall detectability of the lesion should be dependent on its detectability at the oblique-angle projections and the proximity of those projections relative to the central orientation. While the overall detectability of a lesion should increase if its detectability at an oblique-angle projection is higher than at the central projection and vice versa, it should be higher still if the orientation of the oblique-angle projection is close to the central orientation causing its background to have a high correlation with that of the central projection (Thus, a smaller angular separation from the center provided a larger contribution of the correlation of the image information to the combined ROC.)

For the second ROC fusion method, a modification of a recently published Bayesian decision fusion algorithm was used.²⁷ In this method, first the ROC for each angular projection in the training data set of 264 ROIs was computed. For each of the 228 ROIs in the testing data set, a signal-present decision variable was then calculated by determining the response of the image embedded with i th lesion to i th lesion template (λ_1^i) and the corresponding signal-absent response by determining the response of the image itself (without the lesion embedded) to the i th lesion template (λ_0^i). Binary observer decision β_i to the i th image was computed as

$$\beta_i = \text{step}(\lambda_1^i - \lambda_0^i) \Rightarrow \beta_i = \begin{cases} 1 & \text{if } \lambda_1^i \geq \lambda_0^i \\ 0 & \text{if } \lambda_1^i < \lambda_0^i \end{cases} \quad (2)$$

The above equation implies that the threshold for correct observer outcome of an i th image is λ_0^i . The values of probability of true positive, p_d , and of false positives, p_f , corresponding to this threshold were then determined from the ROCs of the 25 angular projections in the training data set. Assuming that the binary decisions were statistically independent, the pdfs of the fused decision variables for signal-present and null hypothesis were then obtained as

$$P(\lambda_{\text{fusion}} | H_1) = \prod_{\theta=1}^{25} (p_d^\theta)^{\beta_i} (1 - p_d^\theta)^{1-\beta_i},$$

$$P(\lambda_{\text{fusion}} | H_0) = \prod_{\theta=1}^{25} (p_f^\theta)^{\beta_i} (1 - p_f^\theta)^{1-\beta_i}, \quad (3)$$

where θ is an index for angular projection. Having found the signal-present and signal-absent decision variables, the pdfs of each were computed from which the combined ROC curve and the AUC were deduced.

The second technique may be understood in the following way: given an image from angular projection, θ , assuming that the decision for signal present is 1, the probability of correct detection is p_d^θ . However, if the decision is 0, the probability that the signal is still present is the probability of false negative and, hence, $(1 - p_d^\theta)$. Thus, the resultant probability of signal present in the image is $p_d^\theta \cdot (1 - p_d^\theta)$. Assuming statistical independence of decisions among angular projections gives the pdfs of the fused decision variables of Eq. (3). In contrast to a genetic algorithm approach used in Ref. 25 to arrive at the binary decision, here we employed a simple thresholding approach that compares signal-present decision variable to a signal-absent decision variable to determine the binary decision.

II.F. Evaluating optimum acquisition parameters

For evaluating the effect of changing operating acquisition parameters on the performance of CI, different combinations of the number of angular projections and the angular spans were considered. A combined ROC was derived for each set of those acquisition parameters using the two ROC fusion methodologies. Finally, the area under each of the combined ROC curves (AUC) was determined as a function of the number of angular projections and the total angular span of those projections. A third-order polynomial fit was applied to fit the existing data points. The combination that yielded the maximum AUC was deemed the optimized acquisition parameters set.

The optimization was evaluated at two dose conditions:

- The isoimage-dose condition in which each angular projection considered for final figure of merit had the same dose level resulting in increasing total dose with each additional angular projection. Under this condition, the performance was evaluated by fusing decisions from N acquisitions. Ignoring the slight variations in dose levels with angular projections,²⁸ the N acquisitions, each at a dose level of D , resulted in a total delivered dose of ND .
- The isostudy-dose condition in which the total dose is divided among the projection images, such that incorporating additional angular acquisition would not result in increased total dose delivered to the patient. While evaluating performance from fusing decisions from N acquisitions, only acquisitions with dose levels of D/N were used, resulting in a fixed total delivered dose of D . Therefore, the optimum number of angular projections and the angular range determined in this case were independent of the dose delivered to the patient.

III. RESULTS

ROC curves and the corresponding AUCs obtained from the three techniques are shown in Fig. 4. The AUC value obtained from a single CC projection was 0.724, while that obtained from the average of 25 ROCs (corresponding to 25 projections) was 0.731. In comparison, the AUCs obtained

FIG. 4. ROCs of 25 projections obtained from a multiprojection imaging system and the average of those. Also shown are the ROCs obtained from the two fusion techniques. The angular span of the projections was 44.8° .

by combining information from 25 projections using the two combination techniques, namely weighted averaging of test statistics and the Bayesian decision fusion technique were 0.905 and 0.915, respectively. These results represent no modification to the dose level of individual projections.

Figure 5 shows variation of the AUC values as a function of the number of projections for different dose levels under isoimage-dose conditions. The total angular span of these projections was fixed at 44.8° . AUC for one projection was computed by averaging the AUCs across all the angular projections within this angular span. The dose level of each acquisition along a curve was constant and corresponded to the fraction of the clinical dose level indicated in the legend. While the AUC values monotonically increase with an in-

FIG. 5. Variation of AUC with a number of projections for different dose levels. Isoimage-dose condition was used implying that the dose level of each projection (D_p) along a curve remains constant (i.e., more projections imply more dose to the patient). This dose level is indicated by the fraction of the clinical dose level in the legend. The Bayesian decision fusion technique was used for this analysis. The angular span of the projections was 44.8° .

FIG. 6. Variation of AUC under isoimage-dose conditions for a different number of angular projections spanning a total angular arc in the 3.6° – 44.8° range using (a) weighted averaging of test statistics techniques and (b) Bayesian decision fusion. The dose level of each acquisition was equal to $1/25$ th of the standard mammographic screening dose level leading to an increased dose level with an increasing number of angular projections considered to reach a maximum of a conventional dual-view screening dose at 25 projections.

crease in the number of projections at lower dose fractions of $1/11$ and less, they appear to approach an asymptote with the increase in the number of projections for dose fractions of $1/7$ and higher. Regardless, the AUC values increase with increasing dose levels.

Figure 6 shows variation of the AUC values with increasing number of angular projections that span different angular arcs in the 3.6° – 44.8° range using (a) the weighted average of test statistics technique and (b) the Bayesian decision fusion technique. In this case, isoimage-dose condition with only one dose fraction of $1/25$ was used. At each angular range, the AUC values increase with the increase in the number of angular projections before reaching an asymptote. The number of projections at which the AUC values peak depends on the angular span. The highest AUC is obtained at an angular span of 44.8° , with 11 projections using Bayesian decision fusion technique and 17 projections with the weighted averaging of test statistics.

Figure 7 shows variation of AUC under isostudy-dose conditions using (a) the weighted average of test statistics technique and (b) the Bayesian decision fusion technique. For all angular spans, the AUC first increases and then decreases as the number of projections is increased. In this case too, the number of projections at which the AUC values peak depends on the angular span. While the maximum AUC

FIG. 7. Variation of AUC under isostudy-dose conditions using the (a) weighted averaging of the test statistics and (b) Bayesian decision fusion technique. The total dose level, equal to 1/25th of the standard dual-view mammographic screening dose level, was linearly divided among the different projections and, hence, the total dose delivered remains constant at this dose level.

value is obtained at an angular span of 44.8° with 16 projections using Bayesian decision fusion technique, the maximum is obtained at just 22.8° with eight projections using the weighted averaging of test statistics technique.

IV. DISCUSSION

The multiprojection imaging technique offers an advantage over single projection imaging techniques in rendering pathology that may be surrounded by a complex cloud of anatomical structures. This is accomplished by exploiting the differences in geometrical perspectives that different projections in a multiprojection scheme offer. Geometrical configuration of the data acquisition therefore plays a pivotal role in the output of a multiprojection system. Image quality in tomosynthesis, for example, can be compromised by an unoptimized data acquisition scheme. In recent implementations of tomosynthesis for breast imaging, while the total dose delivered to the patient has varied between 0.75 and 1 times the standard procedure, the number of angular projections has varied between 11 and 25 with total angular span in the 30°–60° range.^{3,10,29} Because of the flexibility in the ways the images may be captured in a multiprojection system, it is important that an optimum configuration of data acquisition components be selected to realize the full potential of such a system.

The methodology used in this study quantifies the effect of changing the geometry of acquisitions in order to maximize the diagnostic image quality of a multiprojection breast CI system. A noteworthy observation from this analysis was that the two fusion techniques, namely the weighted averaging of test statistics and the Bayesian decision fusion techniques, clearly show improvement in diagnosis when information from multiple images are combined in a multiprojection CI system, indicating potentially improved breast cancer detection using a multiprojection CI system. Since the final clinical decision is based on a collective decision made from detectability cue gathered from each angular projection, it is essential to fuse the 25 ROCs into one final index of performance. The fusion techniques are, therefore, a critical element of such a multiple acquisition setup.

The two fusion approaches buildup on the framework of mathematical observer models that have been shown to correlate with detection performance of human observers on complex anatomical backgrounds. As a result, the Bayesian decision fusion and the weighted averaging of test statistics techniques potentially emulate the decision process used by human observers in arriving at the final decision. However, there are certain differences between the two fusion techniques; while the Bayesian technique draws cues from a training data set to fuse binary detection decisions from each of the 25 angular projections, the second technique explicitly incorporates the effect of correlation between the oblique angle projections and the central projection. While a similar Bayesian decision technique has been reported earlier in the literature,²⁷ the weighted averaging of the test statistics is a novel approach for decision fusion. As such, the two approaches show comparable effects of changing the acquisition scheme on the performance of CI and are expected to correlate with the base line detection performance of a clinician using a multiprojection system.

The ROC fusion techniques developed in this study may be extended to optimize a digital breast tomosynthesis system. An optimization scheme for tomosynthesis would, however, also incorporate the effects of reconstruction inherent in the technique. While this study establishes relative diagnostic performance of a multiprojection acquisition scheme, the findings may not be directly extrapolated to tomosynthesis without taking reconstruction into account. However, in the absence of reconstruction, the present results can be viewed as a reflection of the inherent information content of a multiprojection method.

Comparing CI to tomosynthesis, the absence of the need to reconstruct images thereby avoiding reconstruction artifacts provides an inherent advantage to CI. In addition, in contrast to tomosynthesis in which as many as 50–80 slices may need to be reviewed depending on the size of the breast, a radiologist may be presented with significantly fewer images in CI, potentially improving confidence or even accuracy of a radiologist's decision. We hypothesized that the use of a smaller number of projections in CI compared to that in tomosynthesis may be adequate to sufficiently reduce the influence of anatomical noise to yield superior diagnostic information. This conclusion is further supported by recent

studies that indicate potential improvement in diagnosis by fusing two views in stereo-mammography.^{30,31} Our own study clearly shows a notable advantage of using multiple views as compared to one-view mammography at constant total dose (Fig. 7).

As currently implemented, the fusion techniques show that the diagnostic performance of CI, in terms of detectability of an embedded mass, is dependent on both the number of projections and the total angular span of those projections. As shown in Fig. 6, the AUC first increases with an increase in the number of projections and then appears to reach an asymptote, irrespective of the angular span. This may be because as the number of projections increase, the observer increasingly incorporates information about the anatomical variation in the image until the observer has “learned” sufficient information. Beyond this level of detection, the performance becomes only quantum noise limited and, hence, dose-dependent rather than anatomical noise or projection dependent. Furthermore, the performance at the same number of projections improves with increase in the angular spans. A possible cause of this behavior is that larger angular spans likely provide diagnostic information that may not otherwise be available from smaller angular spans. This pattern, however, reverses as the number of projections decreases: the performance at smaller angular spans is better for a lower number of projections. This may be due to two reasons; first, there is higher correlation between neighboring images spanning a smaller arc than those which are spread along a larger arc, and second, at smaller angles, the x-ray beam has smaller paths resulting in lower attenuation of the beam than encountered at larger angles. This behavior is also seen in Fig. 7 that shows the variation in AUC values under isostudy-dose condition: the AUC values are higher for lower number of projections at a smaller angular span. The most noteworthy observation, however, is the sharp drop in the AUC values with increase in the number of projections, resulting in a bell-shaped characteristic of the AUC values as a function of number of projections. Besides a redundancy in anatomical information with increase in the number of projections, the sharp drop may also be attributed to the fact that although the total dose remains constant in the isostudy-dose condition, the dose level of each projection decreases with the increase in the number of projections, thereby decreasing the detectability due to reduction of the quantum signal-to-noise-ratio at each projection.

The dose dependence of detectability is clear in Fig. 5, which plots the variation of AUC as a function of number of projections for a fixed angular span of 44.8° , but different dose levels. The AUC values are seen to reach an asymptote with an increase in the number of projections, albeit the absolute value of AUC decreases, as expected, with a decrease in the dose level. Most noteworthy is the fact that the inflection point where the AUC maximizes is seen to be different for different dose levels. As a result, although a total of 11 or 17 projections at 44.8° may be deemed an optimized geometry as indicated by Fig. 6, this optimization is dose dependent. This is because the total dose delivered at any projection, under the isoimage-dose condition considered for Figs.

5 and 6, is higher than that delivered at a smaller number of projections. An alternative, however, is the isostudy-dose condition evaluated in this work in which the total dose delivered was constant. Such an evaluation is especially important in light of the observation from Fig. 6 that the performance at smaller angular spans may be better with a small number of projections. A higher total dose level at this number of projections than that possible in the isoimage-dose condition may therefore potentially increase the performance beyond that achieved at 11 or 17 projections with a total angular span of 44.8° . Incidentally, a recent study on the implementation of CI for chest imaging also found a similar number of images to render optimum performance.¹¹

One limitation of this study was our inability to evaluate performance at an arbitrary number of angular projections for each angular span. This is because we were limited by the sampling of the original clinical images which was uniform within each angular span. This is evident in Figs. 6 and 7 where the AUC values were plotted for fewer angular projections for narrower angular spans. Furthermore, we recognize that in the first decision fusion approach based on a weighted average of test statistics, the weights could be defined as a function of other alternatives such as the angular separation, the total number of projections, and a reference projection other than the central projection used for this study. The technique, however, was developed as a first approximation to the actual clinical decision process used by radiologists. In addition, although the observer models have been shown to correlate well with human detection performance on real anatomical backgrounds like mammograms, an exhaustive study has not yet been carried out to conclusively establish the correlation. Furthermore, because we could only simulate a reduction of exposure levels by adding corresponding noise onto the images, only one isostudy-dose condition of the total dose of D_θ could be investigated (D_θ corresponding to 1/25 of standard two-view mammographic screening dose). The isostudy-dose trends thus reported in this study may vary at dose levels close to the clinical dose level. Finally, the optimum acquisition parameters determined for the multiprojection system in this study may not be directly applicable to tomosynthesis. Nonetheless, the methodologies developed in this study may serve as guidelines for optimizing the acquisition parameters and dose for any multiprojection imaging system.

V. CONCLUSIONS

In this study, we developed a framework to optimize the geometry of acquisitions of a multiprojection CI system by combining information from its multiple projections. It was found that the detectability of an embedded mass increased by fusing information from multiple projections demonstrating the feasibility of CI as a potential technique for improved breast cancer detection. The overall performance of the multiprojection system was a function of the number of projections used, the total angular span of those projections, and the acquisition dose level. A key finding in the situation in which the total patient dose increases with the number of

projections was that the detectability approached an asymptote at about 11–17 projections spread over an angular arc of $\sim 45^\circ$. In situations in which the total patient dose was kept constant independent of the number of projections, the performance approximately followed a bell curve with the best detectability obtained with only eight projections spanning an angular arc of $\sim 23^\circ$. The methodology presented here for optimizing acquisition parameters are generic in nature and may be easily adopted for optimizing the acquisition parameters for other multi-imaging techniques.

ACKNOWLEDGMENTS

The authors would like to acknowledge Craig Abbey at UC Davis for his feedback on the observer model workup. Thanks are also due to Jonathan Jesneck for helpful discussions on the Bayesian decision fusion methodology. Thanks to Swatee Singh for collecting and organizing the tomosynthesis data as a part of the ongoing clinical trial at Duke. This work was supported in part by the DOD (Grant No. W81XWH-06-1-0449), NIH (Grant Nos. R01-CA109074 and R01-CA112437), Komen Foundation (Grant No. PDF55806), and Cancer Research Prevention Foundation.

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