Task-based assessment of breast tomosynthesis: Effect of acquisition parameters and quantum noise^{a)}

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Purpose: Tomosynthesis is a promising modality for breast imaging. The appearance of the tomosynthesis reconstructed image is greatly affected by the choice of acquisition and reconstruction parameters. The purpose of this study was to investigate the limitations of tomosynthesis breast imaging due to scan parameters and quantum noise. Tomosynthesis image quality was assessed based on performance of a mathematical observer model in a signal-known exactly (SKE) detection task.

Methods: SKE detectability (d') was estimated using a prewhitening observer model. Structured breast background was simulated using filtered noise. Detectability was estimated for designer nodules ranging from 0.05 to 0.8 cm in diameter. Tomosynthesis slices were reconstructed using iterative maximum-likelihood expectation-maximization. The tomosynthesis scan angle was varied between 15° and 60° , the number of views between 11 and 41 and the total number of x-ray quanta was ∞ , 6×10^5 , and 6×10^4 . Detectability in tomosynthesis was compared to that in a single projection.

Results: For constant angular sampling distance, increasing the angular scan range increased detectability for all signal sizes. Large-scale signals were little affected by quantum noise or angular sampling. For small-scale signals, quantum noise and insufficient angular sampling degraded detectability. At high quantum noise levels, angular step size of 3° or below was sufficient to avoid image degradation. At lower quantum noise levels, increased angular sampling always resulted in increased detectability. The ratio of detectability in the tomosynthesis slice to that in a single projection exhibited a peak that shifted to larger signal sizes when the angular range increased. For a given angular range, the peak shifted toward smaller signals when the number of views was increased. The ratio was greater than unity for all conditions evaluated.

Conclusion: The effect of acquisition parameters on lesion detectability depends on signal size. Tomosynthesis scan angle had an effect on detectability for all signals sizes, while quantum noise and angular sampling only affected the detectability small-scale signals. © 2010 American Association of Physicists in Medicine. [DOI: 10.1118/1.3357288]

Key words: tomosynthesis, prewhitening observer model, structured background, objective assessment

I. INTRODUCTION

Breast cancer screening using x-ray projection mammography has contributed to the reduction in breast cancer mortality.¹ Despite this success, lesion detectability in conventional mammography is limited by the anatomic background structure,² which is caused by the projection of the complex 3D parenchymal structure into a plane. To overcome this limitation, 3D breast imaging techniques are being developed, including breast CT and tomosynthesis.^{3–5}

In breast tomosynthesis, a 3D volume is reconstructed from a limited number of half-cone projections acquired while the x-ray source travels along an arc. Because of the limited arc, depth resolution depends on both scan angle and extent of the structures being imaged. The appearance of the tomosynthesis volume also depends on the number of projection views acquired.^{6,7} Furthermore, the reconstructed image is affected by the choice of reconstruction algorithm. Both analytically based algorithms, including matrix-

inversion tomosynthesis^{8,9} and filtered backprojection (FBP)^{10,11} and iterative algorithms^{12,13} have been applied to tomosynthesis reconstruction. Iterative algorithms tend to provide less artifacts in the reconstructed images based on an initial study.¹⁴

There have been a number of studies investigating the effect of tomosynthesis acquisition parameters on image quality. Ren *et al.*⁶ investigated the effect of number of projection views on contrast-to-noise ratio (CNR) for a fixed dose and 20° angular scan using simulated data and data acquired on a tomosynthesis prototype. In addition, artifact conspicuity was evaluated. Signals were embedded into a uniform phantom, and the breast volume was reconstructed using FBP. No dependence of number of views on CNR was found. The authors point out that the choice of reconstruction filter may play an important role in optimizing image quality.

Deller *et al.*¹⁵ conducted experiments to determine the effect of acquisition parameters on in-slice and depth resolution, noise level, and ripple. Both anthropomorphic phan-

toms and clinical images were used. Images were reconstructed with a generalized FBP algorithm. It was found that depth resolution depended on scan angle, and ripple depended on number of views and background structure.

Sechopoulos and Ghetti¹⁶ used a computer simulation to model tomosynthesis data. The data model included polychromaticity, scatter, detector noise and an angle dependent MTF. The breast model consisted of a structured background that was generated by filtering a random noise volume. A solid sphere and a solid cube were representative of a mass and a microcalcification lesion, respectively. A figure-of-merit, which combined contrast-to-noise ratio and depth resolution, was computed for each configuration and lesion type. They found that (a) increasing the angular range always increased depth resolution, (b) increasing the number of views beyond a “critical number of views” does not increase depth resolution, and (c) minimal number of projections needed to optimize depth resolution was proportional to the angular range. From all configurations studied, 60° and 13 projections resulted in the best image quality.

Zhao *et al.*¹⁷ have developed a 3D cascaded linear systems model for tomosynthesis that they have used to compute the 3D DQE in the reconstructed volume. They found reasonable agreement between their model predictions and experimental measurements. Since the reconstruction is based on filtered backprojection, it could be included in the linear systems model and they were able to study the effect of acquisition parameters and reconstruction filters on 3D DQE.^{7,17,18} It is not clear how iterative algorithms can be incorporated into this model. In addition, this model does not account for nonstationary detector response due to the oblique x-ray incidence.¹⁹

Chawla *et al.*²⁰ investigated observer performance for the task of detecting a 3 mm signal in the projection and reconstructed images. Performance was estimated for the in-focus slice of the signal using a Laguerre–Gauss (LG) channelized Hotelling observer, and a Bayesian fusion observer based on LG channel functions for the projection images. Tomosynthesis projection data of five mastectomy specimens were obtained on a tomosynthesis prototype unit and reconstructed using a FBP-based algorithm. An increase in observer performance with scan angle was found, as well as a plateau in performance as a function of projection views. Observer performance in the reconstructed slice was found to be slightly lower than that in the combined projections.

In this work, tomosynthesis imaging task performance was investigated in the absence of degrading physical effects, to determine the limitations of tomosynthesis due to acquisition geometry only. Actual tomosynthesis projection data are degraded by detector MTF and detector electronic noise, scatter, focal spot blur, and possibly motion blur, which occurs in systems with continuous x-ray source motion. In an actual tomosynthesis system, the x-ray beam is polychromatic.

II. METHODS

Tomosynthesis system performance was assessed by measuring performance in a signal-known exactly (SKE) detec-

tion task for a range of signal sizes in the presence of a structured background. SKE detection task performance, referred to as *detectability* in the following, was estimated using a prewhitening observer model as a surrogate for human observers. The tomosynthesis simulation was based on an ideal data model that consisted of a point x-ray source and an ideal detector that incurred quantum noise only. The simulated projection images were scatter-free. An ideal system is most closely represented by the photon-counting tomosynthesis prototypes, which have inherent scatter rejection.^{21,22} Breast backgrounds and lesions were modeled by adding designer nodules^{2,23,24} to filtered noise structured backgrounds. The tomosynthesis volume was reconstructed using an iterative algorithm at a fixed number of iterations. While the reconstruction algorithm impacts the visual appearance of the tomosynthesis volume,²⁵ the reconstruction algorithm and its parameters were held fixed to be able to assess the effects of scan parameters and quantum noise only.

II.A. Task-based assessment of tomosynthesis image quality

Image quality of the tomosynthesis system was assessed by estimating performance in a SKE detection task. To be able to investigate a large number of acquisition configurations, detectability was estimated using a PW observer model rather than by performing reader studies involving human observers.

SKE detectability of a prewhitening observer (d'_{PW}) is given by

$$d'^2_{PW} = \int_{|\vec{f}|>0} \frac{|S(\vec{f})|^2}{W(\vec{f})} d\vec{f}, \quad (1)$$

where $\vec{f}$ is spatial frequency and $S(\vec{f})$ is the amplitude spectrum of the signal. The background power spectrum $W(\vec{f})$ is estimated through

$$W(\vec{f}) = \langle |\mathcal{F}\{\tilde{r}(x,y) - \langle \tilde{r}(x,y) \rangle\}|^2 \rangle, \quad (2)$$

where $\tilde{r}(x,y)$ is a background region-of-interest (ROI) and $\langle \dots \rangle$ denotes ensemble mean. The background ROI contains both structure and quantum noise. Background ROIs $\tilde{r}(x,y)$ were multiplied with a Hann window²⁶ to reduce spectral leakage.^{27,28}

PW observer performance was computed by numeric integration of Eq. (1). We chose to exclude $|\vec{f}|=0$ since there is a singularity if background ROIs have zero mean. This issue does not arise in another work (see, for instance, Ref. 29) where integration is carried out in polar coordinates and the contribution and the contribution of the integrand at $|\vec{f}|=0$ vanishes. PW observer performance was computed for the log-projection data as well as the reconstructed plane intersecting the signal center.

For SKE detection of additive signals in cyclostationary backgrounds, the PW observer is the ideal observer.^{29,30} For additive signals in mammographic backgrounds, which are not stationary, the PW observer was found to be proportional to a channelized Hotelling observer, an approximation of the

ideal observer.² Furthermore, the PW observer was found to predict human performance in mammographic backgrounds,² and dual energy x-ray imaging.³¹

Human observers predominantly analyze the tomosynthesis volume by scrolling through reconstructed slices. Therefore a 2D observer model was used and detectability was computed for the in-focus slice of the object only, where d' is highest.

Note that for cyclostationary backgrounds, the PW observer is the ideal observer. In this study, the original 3D structured background is cyclostationary. The tomosynthesis reconstruction is a blurred representation of the original volume. Furthermore, Poisson noise was added to the projection data, introducing a dependency on location.

To investigate the effect of Poisson data noise and the limited-angle reconstruction on the stationarity of the reconstructed noisy backgrounds, performance of a non-prewhitening (NPW) observer was computed using a Fourier-domain expression that is valid for stationary backgrounds only and a spatial domain expression that is valid for nonstationary backgrounds.³² In the frequency domain, performance of the NPW observer is²⁹

$$d_{\text{NPW},f}^{\prime 2} = \frac{[\int_{|\vec{f}|>0} |S(\vec{f})|^2 d\vec{f}]^2}{\int_{|\vec{f}|>0} W(\vec{f}) |S(\vec{f})|^2 d\vec{f}}. \quad (3)$$

The equivalent spatial domain expression is

$$d_{\text{NPW},s}^{\prime 2} = \frac{\sum s(r)^2}{\text{var}(\lambda_n)}, \quad (4)$$

where $\lambda_n = \sum_{x,y} s(x,y) \tilde{r}(x,y)$. For stationary backgrounds, spatial domain and spatial frequency expressions are equivalent. For nonstationary backgrounds, detectability computed from the two expressions are not equal.³³ A non-prewhitening observer was used for this comparison, rather than a prewhitening observer because of the simplicity of the spatial domain expression for the NPW observer. The spatial domain expression of a PW observer involves the inverse covariance matrix of the data,³⁰ which is difficult to estimate.

II.B. Tomosynthesis simulation

II.B.1. Tomosynthesis data model

The tomosynthesis projection data g were simulated assuming an ideal x-ray system, i.e., monoenergetic x-rays that originated from a point source were detected by an ideal detector.

The projection data for test images were generated using a software phantom. The phantom contained both analytical and numerical components. Uniform backgrounds and signals were defined through geometric descriptors and projection data were computed analytically. Structured backgrounds were defined through voxel values in a 3D array and projection data were computed using a pixel-driven discrete-to-discrete projector (see Sec. II C 2).

Quantum noise in each detector bin was introduced by sampling from a Poisson distribution with a mean of

TABLE I. Relative glandular dose (RGD) as a function of tomosynthesis scan angle α for an attenuation of $\mu=0.7 \text{ cm}^{-1}$ and a breast thickness of 5 cm.

α	15	30	60	60
n_{view}	11	21	11	41
RGD	0.997	0.989	0.951	0.957

$$g(u,v,\phi) = I_0 w(u,v,\phi) \exp\left[-\int \mu(\vec{r}) dl\right], \quad (5)$$

where I_0 is the photon flux at the central ray and $w(u,v,\phi)$ are weights that account for the solid angle subtended by each detector bin with respect to the x-ray source.³⁴ $\int \mu(\vec{r}) dl$ is the path integral, where the path is a straight line from the source point to the center of the detector bin, and $\mu(\vec{r})$ is the spatial distribution of attenuation coefficients of the object. For image reconstruction, the logarithm of the projection data g' is required, which was computed through

$$g' = -\log\left(\frac{g}{I_0 w(u,v,\phi)}\right). \quad (6)$$

In this data model, photon flux at the central ray (I_0) was constant for all scan parameters for a given photon flux level. As a result, the glandular dose varied for each acquisition. To assess the magnitude of glandular dose variation for different tomosynthesis scan parameters, a simple model was used to estimate the glandular dose in a tomosynthesis projection (RGD(α)), relative to the glandular dose in the center projection. This model assumes that primary radiation is the main cause of glandular dose. This is justified by the results of Boone *et al.*³⁵ which show that energy deposition at shallow depths is predominantly due to the primary radiation for 20 keV x rays.

With this assumption, the Lambert–Beer law can be used to express (RGD(α))

$$\text{RGD}(\alpha) = \cos(\phi_i) * \{1 - \exp[-\mu * t/\cos(\phi_i)]\}. \quad (7)$$

The factor $\cos(\phi)$ is caused by oblique incidence.

The results of this model agree with the Monte Carlo calculation by Sechopoulos *et al.*³⁶ to within 1.6% for angles up to 30°. The average glandular dose per tomosynthesis scan, $\text{RGD}(\alpha, n_{\text{view}}) = 1/n_{\text{view}} \sum_i^n \text{RGD}(\alpha_i)$ for a subset of acquisition parameters is listed in Table I. It shows that the total glandular dose varies less than 5% for the various acquisition schemes.

II.B.2. Reconstruction algorithm

From the data g' , an image $\hat{f}$ was reconstructed iteratively using the update equation

$$\hat{f}^{(k+1)} = \hat{f}^{(k)} \frac{1}{s} M^+ \left\{ \frac{g'}{M \hat{f}^{(k)}} \right\}, \quad (8)$$

where M and M^+ are the projection and backprojection operators, respectively, $s = \sum M^+$, and $g'/M \hat{f}^k$ indicates a division between vector elements. In our implementation, the projector was ray-driven, while the back-projector was voxel

driven.¹³ All images were reconstructed with eight iterations. This is within the number of iterations used by Wu *et al.*²⁵

II.B.3. Tomosynthesis geometry

The tomosynthesis system consisted of an x-ray source moving along an arc of 60 cm radius. The object was centered on the source pivoting point and an ideal detector with 100 μm pixel size was located 6 cm below the pivoting point. The detector was held stationary with respect to the object. Tomosynthesis images with a voxel size of $0.1 \times 0.1 \times 1 \text{ mm}^3$ were reconstructed using ML-EM [Eq. (8)] at eight iterations. Tomosynthesis projections were acquired at a constant total photon fluence relative to the x-ray source center ray. Total photon fluence was divided equally between views.

II.C. Breast model

II.C.1. Lesion model

In previous studies,^{2,23,24} designer nodules were used to investigate lesion detectability in projection images. The signal profile of a designer nodule of radius R is given by

$$s(r) = a * \pi_{2R} \left[1 - \left(\frac{r}{R} \right)^2 \right]^\nu, \quad (9)$$

where a is signal amplitude, ν controls the sharpness of the edge, and π_x is a rect function with $\pi_x=1$ for $0 < r < x$ and $\pi_x=0$ elsewhere. A signal with $\nu=1/2$ corresponds to the projection of a solid sphere.

In this study, lesions were approximated through spheres with spherically intensity distributions with a radial profile given by

$$S(r) = A \left[1 - \left(\frac{r}{R} \right)^2 \right] \pi_{2R}, \quad (10)$$

where A is the amplitude at $r=0$. The normal projection of $S(r)$ is

$$s(r) = \frac{4}{3}AR \left[1 - \left(\frac{r}{R} \right)^2 \right]^{3/2} \pi_{2R}. \quad (11)$$

The projected signal profile $s(r)$ is therefore a designer nodule with $a=AR$ and $\nu=1.5$. Signal projections were computed analytically to avoid discrete-to-discrete projection artifacts in the signal. The use of designer nodules with $\nu > 0.5$ ensures convergence of the integral in Eq. (1) in the absence of quantum noise.²

Signals were added to a uniform background. Log-projections were computed analytically and subsequently reconstructed using Eq. (8). Signal-only profiles used in Eq. (1) were generated by subtracting the uniform background from the signal-plus-background image, using a reconstructed uniform background to obtain the spectrum of the reconstructed signal.

II.C.2. Structured background model

The structured background was derived from a noise volume with random phase and power-law spectrum. These fil-

tered noise backgrounds have been used to simulate breast backgrounds previously.^{16,37} Here, the volume was initialized in the spatial frequency domain as a volume of complex numbers with random phase $\phi=(-\pi, \pi]$ and a power-law magnitude,

$$V(\vec{f}) = \exp(-i\tilde{\phi}) * \frac{c}{|\vec{f} + \vec{f}_0|^{\beta/2}}, \quad (12)$$

where f_0 is a constant to avoid a singularity at $f=0$. The magnitude c and power-law exponent β determine the amplitude and texture of gray values in the volume, respectively. The volume was transformed to the spatial domain through an inverse Fourier transform.

Since breast tissue primarily consists of two tissue types, adipose and fibroglandular, the gray-scale volume was binarized³⁸ by applying a threshold. The threshold value t_d was varied iteratively until the proportion of voxel values above threshold equaled the requested breast glandular fraction d ,

$$d = \frac{N(v > t_d)}{N_x * N_y * N_z}, \quad (13)$$

where v is gray value of a given voxel and $N(\cdot)$ is the voxel count. $N_x * N_y * N_z$ is the volume size in voxel units.

Once the threshold value t_d was determined, attenuation values corresponding to fibroglandular and adipose tissues were assigned to the voxels above and below threshold, respectively. The texture of the volume was determined by the value of β . The parameter c in Eq. (12) is not relevant because it determines the magnitude of variance of the background, which affects the actual threshold value but not the final characteristics (percent glandular fraction, texture) of the volume.

This background was then numerically projected using a ray-driven projector. To reduce artifacts due to the discrete-to-discrete operation, the voxel size was equal to or smaller than the projection pixel size.

Figures 1 and 2 show examples of images generated using this background. Figure 1 shows slices through the volume, as well as tomosynthesis projections and reconstructed slices. Figure 2 shows reconstructed image slices with different levels of quantum noise, as well as one image slice containing a signal.

II.C.3. Background discretization

Structured backgrounds were generated by projecting a 3D array into a plane. This discrete-to-discrete operation can introduce artifacts if the voxel size of the array is too coarse, compared to the pixel size of the plane. To assess this effect, we generated filtered noise volumes with voxel side lengths $|v|$ that were four, two, one, and 0.8 times the side length of a pixel $|p|$. Figure 3 shows the resulting projections. Discretization artifacts can be perceived when $|v|$ is greater than the $|p|$. We also generated background power spectra from the projection from ten noise realizations (Fig. 4). A Hann window was used to prevent spectral leakage. The power spectra

FIG. 1. (a) 80 μm thick slice through the filtered noise volume; (b) 0.8 mm thick slice through the filtered noise volume, obtained by adding ten slices; (c) tomosynthesis center projection; (d) tomosynthesis reconstructed slice from 41 projections across 60° . ROI side length is 2.5 cm.

reflect the artifacts seen in the projection images. Based on these results, filtered noise volumes with $|v|=0.8|p|$ were generated for the performance calculation.

II.D. Data analysis

For a linear observer model, detectability (d') is proportional to signal amplitude a . This linearity can be exploited

FIG. 2. Tomosynthesis reconstructed slices from a 60° , 11 view scan. (a) Filtered noise only. (b) $\Phi=6 \times 10^5$, (c) $\Phi=6 \times 10^4$, (d) $\Phi=6 \times 10^4$, and 0.8 cm signal diameter. ROI side length is 5 cm.

FIG. 3. Projections generated from a discrete 3D array. (a): $|v|=4|d|$, (b): $|v|=2|d|$, (c): $|v|=1|d|$, (d): $|v|=0.8|d|$.

to determine the *amplitude threshold* (a_t) that is needed to reach a constant detectability d' . The value of d' is arbitrary, and was chosen to be $d'=2$ in this work to be consistent with Ref. 2. Amplitude threshold was determined by

$$a_t = \frac{2}{d'} a, \quad (14)$$

where a is the signal amplitude that produces a detectability of d' . A plot of a_t versus R (signal radius) is a contrast-detail diagram.

For SKE detectability in power-law backgrounds, Burgess *et al.* have derived a relationship between a_t and signal radius R ,

$$\log(a_t) = C + m \log(R), \quad (15)$$

where C is a constant for a given signal shape and power spectrum exponent and m depends on the power spectrum

FIG. 4. Background power spectra of images generated through a discrete-to-discrete projection from a voxelized background. (a): $|v|=4|d|$, (b): $|v|=2|d|$, (c): $|v|=1|d|$, (d): $|v|=0.8|d|$.

TABLE II. Acquisition parameters used in a selection of tomosynthesis prototypes.

α	n_{view}	Reference
13	48	41
15	11	42
50	49–25	43
50	11	25

exponent of the background (β) through $m=(\beta-2)/2$ [see Eq. (12)].² The dependence of m on β has been verified for values of β ranging between 1.5 and 3.5 and signal diameters between 8 and 128 pixels for both human and model observers.²⁴ For uncorrelated white noise, $\beta=0$ and $m=-1$, i.e., the slope of the CD diagram is negative. For $\beta>2$, the slope of the CD diagram is positive. Note that in this formalism, signals have a profile with a maximum of 1 that is multiplied by a_t .

To be able to plot a contrast-detail diagram for signals defined in 3D, amplitude of the projected signal was computed using Eq. (11) at $r=0$ and threshold amplitude was determined through

$$a_t = \frac{2}{d'} a = \frac{2}{d'} \frac{4}{3} AR. \quad (16)$$

III. MATERIALS

III.A. Object parameters

PW observer performance was estimated for signals of diameters of 0.05, 0.5, 0.2, 0.4, and 0.8 cm. The smallest diameter corresponds to a large microcalcification. Smaller signal sizes were not included because of sampling, and results depend on the relative location of the signal center on the detector grid. The upper limit of signal size is that of a small mass lesion.

Structured backgrounds were generated using $\beta=3.1$ and $d=0.75$ to represent high-risk parenchymal structure.^{28,39} The attenuation coefficients for both tissue types at 20 keV were $\mu_{\text{fatty}}=0.456 \text{ cm}^{-1}$ and $\mu_{\text{gland}}=0.802 \text{ cm}^{-1}$.⁴⁰

III.B. Acquisition parameters

A number of tomosynthesis prototype have been described in the literature, using a variety of scan parameter. Table II lists the scan angles and number of views of a selection of prototypes. This list is not intended to be complete but to show the variety of systems. The acquisition parameters investigated in this work are listed in Table III. They were chosen to cover the range of acquisition schemes used in current prototypes.

III.C. Quantum noise

To investigate the effect of quantum noise on detectability, three different x-ray fluence levels were chosen: (1) $\Phi=\infty$, (2) $\Phi=6 \times 10^5$ photons/pixel, and (3) $\Phi=6 \times 10^4$ photons/pixel.

TABLE III. Scan angles (α), number of views (n_{view}), and angular sampling distance ($\Delta\alpha$) investigated in this study. All angles are in degrees.

α	n_{view} ($\Delta\alpha$)
15	11 (1.5), 21 (0.75)
30	11 (3), 21 (1.5)
60	11 (6), 21 (3), 41 (1.5)

To put these fluence levels into a context, in screen-film mammography, an incident fluence of $\Phi=5.86 \times 10^5$ photons/(0.1 mm)² results in an exposure to the detector of 15 mR for a 5 cm thick breast with 75% glandular fraction ($\mu=0.71 \text{ cm}^{-1}$ at 20 keV), assuming a bucky factor of 2. This detector exposure is typical for mammography.⁴⁴

IV. RESULTS

To assess the stationarity of the simulated backgrounds used in this study, detectability of a non-prewhitening observer was computed using spatial and spatial frequency domain expressions [Eqs. (3) and (4)]. The results are shown in Fig. 5 for a signal of 0.2 cm diameter added to structured background samples reconstructed from projections with $\Phi=6 \times 10^4$ photons/pixel. Variance in d'_{NPW} was estimated from 100 bootstrap samples. Performance of both spatial and frequency domain expressions overlap within error bars. Therefore the reconstructed backgrounds can be considered approximately stationary, which validates the expression used to compute d'_{PW} in this study.

Figure 6 shows d'_{PW} in the reconstructed slice, as a function of number of background samples. The length of the error bars represent one standard deviation. Variance in d'_{PW} was estimated from 1000 bootstrap trials.⁴⁵ We found that for 20 samples, bias was below 6.3% and the relative error was below 3.5%, for all signal sizes. All data presented in the following were estimated using 20 background samples.

Fig. 5. Detectability of a non-prewhitening observer model computed using spatial domain and frequency domain expressions for a signal of 0.2 cm diameter. The length of the error bars is 2σ .

FIG. 6. PW observer performance as a function of number of background samples for all signal sizes (signal diameter 0.05–0.8 cm). The length of the error bars is $2 \cdot \sigma(d'_{PW})$.

Amplitude thresholds in a single zero degree projection ($\alpha=0$, $n_{\text{view}}=1$) is shown in Fig. 7. In the absence of quantum noise, a linear relationship between $\log(a_t)$ and $\log(d)$ (with $d=2R$) is observed, in agreement with Ref. 24. As quantum noise increases, amplitude thresholds for smaller scale signals (diameter below 0.2 cm) increase because the signal becomes harder to detect. Amplitude thresholds for the larger scale signals are little affected by the presence of quantum noise. The departure from linearity for the smallest signal in the absence of quantum noise is likely due to sampling effects.

Figure 8 shows amplitude thresholds for detection in the tomosynthesis slice through the center of the signal. The two top panels and left bottom panels show detection performance for different tomosynthesis scan angles, while the angular sampling distance was held fixed in the bottom right panel ($\Delta\alpha=1.5^\circ$).

In all tomosynthesis slices, the same general trends as in the center projection can be observed: a_t increases with signal size and depends strongly on quantum noise for small-scale signals. Amplitude thresholds of large signals are little affected by quantum noise.

For all scan parameters at $\Phi=6 \times 10^4$, a_t exhibits a minimum at $d_0=0.2$ cm. This is due to the two background noise components, namely, quantum and structure noise. For pure quantum noise, the slope in the CD diagram is negative,

FIG. 7. Signal detectability in a single zero degree projection ($\alpha=0$, $n_{\text{view}}=1$) for different exposure levels.

FIG. 8. Signal detectability in the reconstructed tomosynthesis slice, for different tomosynthesis scan angles, number of view, and photon fluence. The bottom right graph shows detectability for a fixed angular sampling distance.

while it is positive for pure structure noise with $\beta > 2$ (see Sec. II D). Quantum noise is the dominant noise source at high spatial frequencies. The transition point is determined by the relative magnitude of the two noise sources. For $\Phi=6 \times 10^4$, this transition point occurs at a spatial frequency of about 1 cycle/mm.

In addition, the effect of acquisition parameters on detectability become apparent. Across all noise conditions, a_t increases as the scan angle decreases, for signals with diameters greater than 500 μm . This effect is particularly pronounced for large-scale signals, regardless of quantum noise, as can be seen for $\Delta\alpha=1.5^\circ$. The number of projection views has a negligible effect on the amplitude thresholds of large-scale signals.

For small-scale signals, the angular range has little effect when the quantum noise is high ($\Delta\alpha=1.5^\circ$, $\Phi=6 \times 10^4$). For small-scale signals at $\Phi=\infty$ and $\Phi=6 \times 10^5$, a_t decreases with increasing scan angle α for fixed angular sampling distance $\Delta\alpha$, and a_t decreases with number of views for constant scan angle α . However, as quantum noise increases, the effect of number of views on a_t diminishes for all signal sizes. An exception is the configuration $\alpha=60^\circ$ for high quantum noise ($\Phi=6 \times 10^5$). Decreasing the number of views from 21 to 11 increases a_t (indicating that detectability is reduced when decreasing the number of views). This indicates that the sparse angular sampling ($\Delta\alpha=6^\circ$) of this configuration causes degradation of performance and implies that $\Delta\alpha \lesssim 3^\circ$ is required to avoid artifacts from insufficient sampling at these noise levels.

To compare signal detectability in tomosynthesis and projection imaging, the ratio of d'_{PW} in the tomosynthesis slice to that in a single projection ($\alpha=0$, $n_{\text{view}}=1$) was computed. As shown in Fig. 9, this ratio never dropped below unity, indi-

FIG. 9. Ratio of signal detectability in the tomosynthesis slice to that in the projection images, when an equal number of photons was used to generate the image.

cating that signal detectability is improved in tomosynthesis over projection imaging, for all signal sizes and acquisition parameters. Overall, $d'_{\text{slice}}/d'_{\text{proj}}$ increases with tomosynthesis scan angle. Increasing the number of views increases this ratio when quantum noise is low ($\Phi=6 \times 10^5$ and $\Phi=\infty$), but has no effect when quantum noise is high, $\Phi=6 \times 10^4$ (an exception is at 60° , 11 versus 21 views). For finite incident photon fluence, the curves exhibit a broad maximum that shift toward larger signal diameter as scan angle increases (except for $\alpha=15^\circ$ and 21 views), and for a given scan angle, increasing the number of views shifts the maximum toward smaller signal sizes. We remind readers that these results are for a tomosynthesis data model that examines only quantum noise and scanning geometry. It does not yet include the effects of spectra, detector noise, scatter, focal spot blurring, and detector characteristics.

V. DISCUSSION

The purpose of this study was to investigate tomosynthesis SKE detection performance in the absence of degrading physical effects, to determine the limitations of tomosynthesis imaging due to acquisition geometry.

In the absence of quantum noise, when the sampling frequency is sufficiently small, the near-linear relationship between $\log(R)$ and $\log(a_r)$ is observed in the reconstructed slice, similar to the projection data (Fig. 7). While the detectability of large-scale signals is primarily affected by scan angle, detectability of small-scale signals is limited by both

quantum noise and angular sampling (i.e., number of views). Insufficient angular sampling degrades detection performance of small-scale signals when there is no or little quantum noise ($\Phi=6 \times 10^5, \infty$). At higher quantum noise levels ($\Phi=6 \times 10^4$), increasing the number of views does not increase detectability and Sechopoulos' *et al.*¹⁶ result of a “threshold number of views” is found, beyond which increasing the number of views does not improve the tomosynthesis images. This is also in agreement with findings of Ren *et al.*⁶ and Chawla *et al.*²⁰

The ratio of detectability in the slice to that in the projection image has also been investigated by Ruschin *et al.*⁴⁶ They found that a factor of 4 higher amplitude was required to reach equal performance for human observers in a projection image, compared to a tomosynthesis reconstructed slice. Their signal consisted of a simulated irregular tumor of about 8 mm diameter, with constant intensity in 3D. The tomosynthesis volume was reconstructed from a 50° scan with 25 views using a reconstruction algorithm based on filtered backprojection.¹¹ In contrast, this study found a lower increase in detectability for 8 mm diameter signals. An increase of a factor of 4 was found for signal diameters of 0.1 and 0.2 cm, for a 60° , 21-view scan at $\Phi=6 \times 10^5$. This discrepancy may be due to different signal profiles. The designer nodules used in this study were less sharp than the signals used in Ruschin's study. In addition, we used a different reconstruction algorithm that is likely to have affected the results.^{25,47} FBP-based algorithms tend to emphasize edges, compared to the ML-EM algorithm used in this work.¹⁴

Tomosynthesis image quality was quantified through detectability in the slice through the center of the signal. Signal detectability in the center slice was found to be higher than in adjacent slices. We plan to investigate the effect of providing adjacent slices to human readers in a separate study in the future.

Detectability computed from a single slice provides information on depth resolution. This research found an increase in detectability with scan angle for all signal diameters greater than $500 \mu\text{m}$. Previous research found an improvement in depth resolution with increased scan angle.^{15,18,41} Both results are equivalent because greater depth resolution results in higher signal contrast. This can be understood by considering the projections of a tomosynthesis volume acquired with different scan angles. Gray values of the center log-projection are approximately equal to path integrals through the volume, and do not depend on scan angle but only on the properties of the object. The projection of a signal can be simplified as being the product of signal spread times signal contrast. Reducing signal spread (i.e., improving depth resolution), therefore, improves signal contrast. Thus, through its dependence on signal contrast, detectability in the slice accounts for depth resolution.

While this study did not include any physical factors other than quantum noise, we plan to investigate the effects of detector blur using a detector model that accounts for oblique incidence.⁴⁸ We anticipate that this will mostly affect small-

scale signals. We will also include the effects of detector noise that will likely affect the results for different number of views. Furthermore, the reconstruction method used in this study was fixed, and the reconstruction method used may not be optimal for tomosynthesis. We have recently developed an iterative reconstruction algorithm based on total variation minimization,¹³ and we will assess detection performance of this new algorithm in a future study.

VI. CONCLUSION

Our results indicate that in the absence of quantum noise, insufficient angular sampling is the predominant source of detectability degradation. Increasing the angular scan range increased d' for all signal sizes. Quantum noise generally deteriorated d' for small signals, if the angular sampling was sufficient. The ratio of detectability in the slice to that in a single projections exceeded unity for all acquisition parameters investigated, and it increased for larger scan angles. Furthermore, this ratio exhibited a peak that shifted toward larger signal sizes as scan angles increased. For a given scan angle, increasing the number of views shifted the peak toward smaller signals. A limitation of these findings is that they result from an investigation of model observer performance in images of simulated backgrounds and lesions.

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