Simple method for computing scattered radiation in breast tomosynthesis

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Purpose: Virtual clinical trials (VCT) are a powerful imaging tool that can be used to investigate digital breast tomosynthesis (DBT) technology. In this work, a fast and simple method is proposed to estimate the 2D distribution of scattered radiation which is needed when simulating DBT geometries in VCTs.

Methods: Monte Carlo simulations are used to pre-calculate scatter-to-primary ratio (SPR) for a range of low-resolution homogeneous phantoms. The resulting values can be used to estimate the 2D-distribution of scattered radiation arising from inhomogeneous anthropomorphic phantoms used in VCTs. The method has been validated by comparing the values of the scatter thus obtained against the results of direct Monte Carlo simulation for three different types of inhomogeneous anthropomorphic phantoms.

Results: Differences between the proposed scatter field estimation method and the ground truth data for the OPTIMAM phantom had an average modulus and standard deviation of over the projected breast area of $2.4 \pm 0.9\%$ (minimum -17.0%, maximum 27.7%). The corresponding values for the University of Pennsylvania and Duke University breast phantoms were $1.8 \pm 0.1\%$ (minimum -8.7%, maximum 8.0%) and $5.1 \pm 0.1\%$ (minimum -16.2%, maximum 7.4%), respectively.

Conclusions: The proposed method, which has been validated using three of the most common breast models, is a useful tool for accurately estimating scattered radiation in VCT schemes used to study current designs of DBT system.

Key words: scattered radiation, SPR, Monte Carlo simulations, anthropomorphic breast models, virtual clinical trial

1. Introduction

Radiological images, such as mammograms and breast tomosynthesis projections, are created within image receptors using the energy deposited from primary and scattered x-ray photons. The distribution of primary x-ray photons contains useful information to visually separate the different tissue types in an x-ray image. However, scattered x-ray photons act as an undesirable signal that degrades the image quality affecting both low (e.g. masses) and high (e.g. calcifications and small fibres) frequency objects, and therefore diagnostic effectiveness is also compromised^{1,2}. In digital systems, the scatter degradation is typically quantified using the differential signal-to-noise ratio (SNRd) or contrast-to-noise ratio (CNR)^{3,4,5}. Such reduction in CNR due to scattered radiation has been quantified up to 54% in digital breast tomosynthesis (DBT) for a 50 mm thick breast⁶. For these reasons, scatter estimation in breast x-ray imaging has been a topic under investigation for many years^{7,8,9,10,11,12,13}.

Estimation of scattered radiation can lead to scatter signal reduction strategies in clinical environment^{14,15,16,17,18,19}, however, it can also help in the design of image simulation frameworks by enabling the addition of the correct amount of scattered radiation in simulated image data^{20,21,22,23,24}. Some of these frameworks are used within virtual clinical trials (VCTs) for lesion detection performance^{23,24,25,26}. This work is concerned with fast schemes to estimate the background scatter contribution to images for use in VCTs. Since the scattered radiation can have a comparable or higher contribution to the total DBT image than the primary signal in the thickest breasts¹¹, it is crucial to estimate this signal properly in order to simulate realistically x-ray breast images.

Typically, conventional 2D mammography employs geometrical rejection (i.e. anti-scatter grids) to reduce the amount of scattered radiation arriving at the image receptor. In this modelling situation, for a constant thickness phantom, the use of a uniform scatter signal in the central area of the image can be considered²⁷. However, most DBT geometries do not

include such geometrical rejection and the scatter variation across the projected breast area should be taken into account^{9,11,12,28,29,30}. A fall of more than 50% can be observed at the chest wall, whereas the scatter signal increases considerably near the borders of the breast, mostly due to the scattered radiation arising from both the compression paddle and breast support^{7,11,30}. Also, the use of tilted compression paddles can vary the scattered radiation distribution³¹. Therefore, scattered radiation is typically estimated via software in DBT.

Various approaches have been made to estimate the variation of the scatter across the projection images acquired in DBT. Direct Monte Carlo simulations using a realistic anthropomorphic model of the breast can be very time consuming unless considerable computing resources are available. It is therefore of interest to explore approaches using simplified models of the breast or results which have been pre-calculated. The work of Sechopoulos and colleagues used simple breast phantoms to provide data for use in scatter correction. Sechopoulos et al¹¹ proposed equations, for both cranial-caudal and mediolateral-oblique views, to estimate the scatter field at the centre of mass based on a curve fitting approach. These multiparameter equations depend on compressed breast thickness (T) and projection angle (θ), and assume homogeneous breast models. Feng and Sechopoulos¹⁴ later developed a method which uses image registration algorithms to match image contours with the pre-calculated scatter-to-primary ratio (SPR) maps from direct Monte Carlo simulations. In an extended version, Feng et al¹⁵ reduced the computational time by generating a scatter map library from principal component analysis-based breast models. In both publications, image quality improved after the reconstruction process. Diaz et al¹² suggested another accurate and fast method for scatter field estimation based on a pixel-wise image convolution which takes into account breast thickness, volumetric glandularity (G), projection angle and breast curvature using a realistic geometry. More recently, Kim et al¹⁹ proposed an iterative scatter correction method using a fibroglandular-adipose tissue ratio model based on graphics processing unit Monte Carlo simulations, which reduce significantly the computational time. The use of such simple and fast schemes for VCTs is attractive, but the question remains

whether scatter estimations based on simple breast models agree sufficiently well with full Monte Carlo calculations using the same anthropomorphic breast model used in a VCT.

In this work, a new fast method is proposed to accurately estimate scattered radiation for realistic DBT geometries for use in VCTs. This is achieved using normalised scatter maps from pre-calculated Monte Carlo simulations of low resolution homogeneous phantoms. The method relies on the assumption that the scattered radiation produced from such simplified phantoms approximates well the scatter generated from anthropomorphic heterogeneous breast models³². This has been tested by comparing the results with full Monte Carlo simulations using the OPTIMAM anthropomorphic breast phantom³³ and then validated using two other commonly used anthropomorphic breast phantoms^{34,35}.

II. Materials and methods

The spatial distribution of the SPR across the receptor plane has been calculated using Monte Carlo using breast phantoms of uniform composition and the results used to estimate the scatter distribution produced by a series of OPTIMAM anthropomorphic breast phantoms³³. The method has been validated for a range of breast thicknesses, glandularities and DBT projection angles by comparison with the results of full Monte Carlo simulations of scatter produced by this series of phantoms. Further validations were then performed using two other types of anthropomorphic breast phantom.

II.A. Monte Carlo simulation and geometry

The DBT geometry of the Hologic Dimensions Selenia x-ray system (Hologic, Inc; Bedford, Massachusetts, USA) has been implemented in a Monte Carlo radiation transport package. Following the American Association of Physicists in Medicine (AAPM) Task Group #268

recommendations³⁶, the details of the simulation are described below.

The simulated setup (Figure 1) included an infinitesimal point x-ray source located at a distance of 700 mm from the receptor plane, a 2.8 mm thick compression paddle (24x18 cm²; polycarbonate with density 1.2 g/cm³), a compressed breast model (details provided in the next section), a 1 mm thick breast support (29x24 cm²; carbon fibre with density 1.8 g/cm³), a 24 mm air gap between support and detector, and finally a detector corresponding to a 200 μ m thick layer (24x18 cm²; selenium) with its corresponding cover. The x-ray beam was collimated to match the compression paddle dimension (24x18 cm²), which was directly in contact with the top surface of the breast model. The rotation point of the DBT system was located in the middle of the detector layer and projection angles of 0, 7.5 and 25 degrees were simulated. Although the Hologic Dimensions Selenia system works typically in the ± 7.5 degrees range, a 25 degrees projection angle was included to investigate the widest projection angles used by other DBT vendors (e.g. Siemens Mammomat Inspiration (Siemens Healthcare GmbH; Erlangen, Germany))³⁷.

Figure 1: Schematic diagram of the geometry used in the Monte Carlo simulations in (a) sagittal and (b) coronal view. The detector tilts with projection angles. Note that the figures are not in scale.

The Monte Carlo simulation toolkit used was Geant4 (10.02.patch-02; June 2016)^{38,39} with the Geant4 physics package option 4 (default particle cut-off of 1 mm). This model uses

the most accurate standard and low-energy models (e.g. atomic deexcitation) for particle simulations within the mammographic energy range. In order to speed up the simulation time, secondary particles (e.g. fluorescence, electrons, etc.) were assumed to be locally absorbed. Since the sensitive layer of the detector was made of Se (K-edge of 12.658 keV), these secondary particles will not travel very far at this energy, and local absorption was assumed. This has been internally tested by us and differences of 0.01% in energy deposition were observed.

This Geant4 code has been previously validated using AAPM’s reference dataset⁴⁰ and implemented for other scattered radiation related studies^{18,41}. Experiments were run using sufficient events (between 15×10^9 to 20×10^9 depending on breast thickness) to produce average standard errors of the mean (SEM) below 1.5% for primary and scatter signals for each 1 mm^2 pixel within the projected breast area. The simulations were run using an Intel Xeon CPU E5-2630 v4 @ 2.20GHz and the computing times for simulation were 10-15 hours and 6-7 hours per projection for high and low resolution breast phantoms respectively, as described in the next section.

Energies deposited within the Se layer (pixel size of 1 mm^2) by both primary ($P(x, y)$) and scattered ($S(x, y)$) photons from the geometry were scored independently. All photons undertaking a scatter interaction (coherent or incoherent) above the detector volume were labelled as scattered photons. Otherwise they were considered primary photons. Since the scattered radiation in the image varies slowly with position, a large pixel size was used^{11,12}. The resulting values of $S(x, y)$ and $P(x, y)$ were combined for each pixel to produce a $SPR(x, y)$ map.

The x-ray energy spectra used were obtained from Boone et al⁴². Appropriate filtration was added to match the measured first half-value layer (HVL)⁴³ and better represents the spectra found on the Hologic system. Table 1 details the beam quality used for each of the breast phantom models simulated.

151 II.B. Breast models

152 The method was developed using ground truth data calculated using OPTIMAM heteroge-
 153 neous anthropomorphic breast models (Elangovan et al³³). These are the models we use in
 154 our VCTs^{23,44}. The external shape of these models was extracted from thresholded DBT
 155 reconstructed volumes. The breast skin was modelled as a 1.5 mm thick layer and the voxel
 156 size was $500 \times 500 \times 500 \mu\text{m}^3$. Different glandularity distributions (P1, P2, P3) for a given vol-
 157 umetric glandularity were produced to investigate variation in the scatter field distribution
 158 under these conditions. Sample central slices of the models are shown in Figure 2(a-c).

Figure 2: (a-c) Central slices of 6 cm thick compressed voxelised breast phantoms, 12 cm radius and volumetric glandularity 17% using different patterns (P1-P3). The corresponding homogeneous breast model is shown in (d). Note that the homogeneous breast has a lower resolution. Sample slices of breast models developed at UPenn³⁴ and Duke University³⁵ are depicted in (e) and (f), respectively. The different tissues has been indicated: Skin, fibroglandular tissue (FT), adipose tissue (AT), Cooper's ligaments (CL), blood vessels (BL) and adipose cavities (AC).

159 The labels associated with each voxel in the heterogeneous phantoms corresponded to:
 160 adipose tissue, fibroglandular tissue, skin, blood vessels and Cooper's ligaments. Each model
 161 also had an associated T, G and an estimated radius (R) corresponding to the distance from
 162 the chest wall to the nipple. The thicknesses, radii and volumetric glandularities for the
 163 different breast models studied are given in Table 1. Note that for selected phantoms, more
 164 than one glandularity was investigated to analyse the effects of glandularity on the scattered
 165 radiation distribution.

Table 1: Configuration of breast phantoms and energy spectra used in this work.

Phantom	T (cm)	R (cm)	G (%)	Volume (cm ³)	Energy spectrum (1 st HVL)
Elangovan et al ³³	3	4 8	35	73.05 286.12	28 kVp W/Al (0.49 mm Al)
	6	8 12	17 2, 17, 40	572.00 1,069.74	33 kVp W/Al (0.59 mm Al)
	9	12 16	9	1,604.51 2,837.72	42 kVp W/Al (0.73 mm Al)
Bakic et al ³⁴	5	5	20	225.57	31 kVp W/Al (0.55 mm Al)
Li et al ³⁵	6	9	32	539.08	33 kVp W/Al (0.59 mm Al)

The low resolution homogeneous models used to approximate the SPR and scatter had a voxel size of 2000x2000x2000 μm^3 and the external shape matched to the anthropomorphic model that was being simulated. The volumes of these models were filled with uniform tissue with glandularity equivalent to the average glandularity of the heterogeneous model (Figure 2(d)). The skin voxels were not modified and therefore included in the uniform tissue.

In order to investigate the adaptability of the proposed methodology, two other breast models were investigated. First, a compressed 5 cm thick breast model of glandularity 20% developed at the University of Pennsylvania (UPenn)³⁴. This phantom had a voxel size of 500x500x500 μm^3 and contained 6 tissue types (skin, fibroglandular and adipose tissue, ducts, cavities and ligaments). Secondly, a compressed 6 cm thick breast phantom developed at Duke University³⁵ with a glandularity of 32%. In this phantom each voxel had a label indicating the percentages of fibroglandular and adipose tissue present (100/0, 75/25, 50/50, 25/75, 0/100) or skin. Central slices of the two phantoms are shown in Figure 2 (e) and (f), respectively.

For all the breast models, the compositions of skin, adipose and fibroglandular tissue from Hammerstein et al.⁴⁵ were used. Cooper's ligaments and blood vessels were assumed to have the composition of adult skeletal muscle from ICRU Report 46⁴⁶, as previously

184 suggested by Ullman et al⁴⁷. Ducts were simulated using fibroglandular tissue and adipose
 185 tissue was used for cavities.

186 II.C. Simple scatter calculations

187 The method estimates the scattered photons distributions for the heterogeneous models
 188 (subscript *het*) using information from prior Monte Carlo simulations generated for the
 189 equivalent homogeneous phantom (subscript *hom*) of lower resolution. After each Monte
 190 Carlo simulation experiment using the homogeneous phantom, $P(x, y)$ and $S(x, y)$ are stored
 191 and $SPR(x, y)$ is calculated as described in section 2.1. Then, a 2 x 2 cm² ROI located in
 192 the detector plane at a distance R/2 from the chest wall is used to calculate the average
 193 scatter (S_{homROI}) and SPR (SPR_{homROI}) signal.

$$194 \quad S_{homROI} = \frac{\sum_{ROI} S(x, y)}{N_{ROI}}, \quad (1)$$

$$195 \quad SPR_{homROI} = \frac{\sum_{ROI} SPR(x, y)}{N_{ROI}}, \quad (2)$$

196 where N_{ROI} is the number of pixels included within the ROI, i.e. 400 for the 1 mm² pixels
 197 image used in the simulations. This ROI is used as a reference area centred in each projected
 198 image. It is used as described below to normalise the SPR and scattered radiation images. In
 199 order to keep the ROI centred, avoiding the edges of the breast image, it is shifted laterally
 200 for projection angles greater than 0 degrees. This displacement was calculated using the
 201 projection of a central point at half height of the breast. Sample ROIs for 0 and 25 degrees
 202 projection angles are shown in figure 3(a).

203 The first stage in the calculation of the scatter for the inhomogeneous phantom is to
 204 normalise the homogeneous scatter map to the average scatter within the ROI using S_{homROI} :

Figure 3: (a) Projected breast contours and corresponding ROIs for projection angles of 0 and 25 degrees are illustrated in green and red, respectively. (b) Normalised scatter map, $S'_{hom}(x, y)$, for an homogeneous phantom (T = 6 cm; R = 8 cm; G = 17%) at $\theta = 0$ degrees. The contour of the projected breast is shown in green and the white lines correspond to the location of intensity profiles shown below.

$$S'_{hom} = \frac{S_{hom}(x, y)}{S_{homROI}}. \quad (3)$$

To estimate the scatter signal in the corresponding heterogeneous model (S_{hetROI}), the primary radiation map within the ROI (P_{hetROI}) is calculated using a ray tracing algorithm (Siddon 1985⁴⁸) and then multiplied by the average SPR in the ROI (SPR_{homROI}) :

$$S_{hetROI} = SPR_{homROI} \times P_{hetROI}. \quad (4)$$

Finally, the scatter signal across the breast phantom, $S_{het}(x, y)$, can be estimated as:

$$S_{het}(x, y) = S'_{hom}(x, y) \times S_{hetROI}. \quad (5)$$

This process was implemented using Matlab R2018a (MathWorks; Natick, Massachusetts, USA) and the 2D scattered radiation distribution was calculated in 15-20 seconds using the pre-calculated Monte Carlo data. A sample distribution of $S'_{hom}(x, y)$ is shown in Figure 3(b).

216 In order to evaluate the accuracy of the proposed scatter field estimation, relative error
 217 maps ($\epsilon_s(x, y)$) were calculated between the proposed method ($S_{het}(x, y)$) and direct Monte
 218 Carlo simulations using the corresponding heterogeneous phantom ($S_{hetMC}(x, y)$), where the
 219 latter represents the ground truth:

$$220 \quad \epsilon_S(x, y) = \frac{S_{het}(x, y) - S_{hetMC}(x, y)}{S_{hetMC}(x, y)} \times 100. \quad (6)$$

221 A target ϵ_S of 10% is proposed as an acceptable error. Since SPR values range between
 222 0.2 and 1.4 in DBT geometries for breast thicknesses between 2 to 8 cm¹¹, a 10% error
 223 corresponds to errors between 3 and 5.5% in the final P+S image.

224 III. Results

225 III.A. Scatter fields comparison of homogeneous and voxelised 226 phantom

227 Figure 4 shows sample intensity profiles of $S'_{hom}(x, y)$ for different breast thicknesses , glan-
 228 dularities and projection angles. Note the similar normalised signal intensity between them
 229 within most of the projected breast area thanks to the normalisation scheme used, with the
 230 largest differences occurring near the edges of the breast model (dashed vertical lines).

231 Figure 5 shows the value of the relative error $\epsilon_S(x, y)$ of the estimated scatter field for
 232 selected breast models of different sizes and glandularities for the 0 degree projection angle.
 233 Signed maps are presented and only values within the projected breast area are shown. Such
 234 breast areas were automatically segmented using thresholding. The legends represent the
 235 relative error in percentage. Overestimation of the scatter method is shown as positive values
 236 (green, yellow, orange), while underestimation is shown as negative values (cyan, light and

Figure 4: Horizontal (first column) and vertical (second column) intensity profiles of $S'_{hom}(x, y)$ as illustrated in Figure 3(b). First and second rows correspond to a phantom of $T = 6$ cm, $R = 12$ cm and different glandularities (2, 17 and 40%) simulated at $\theta = 0$ and $\theta = 25$ degrees, respectively. Bottom row (e-f) represents phantoms of $R = 12$ cm and thickness of 6 cm ($G = 17\%$) and 9 cm ($G = 9\%$) for $\theta = 0$ degrees. Vertical dashed lines represent the projected edge or boundary of the phantom.

dark blue). A zero error is shown as green. To calculate these differences quantitatively, the average and standard deviation of the modulus is calculated within the projected breast region. The observed modular average and standard deviation differences are $1.6 \pm 1.3\%$ (minimum -5.9%, maximum 19.3%), $2.7 \pm 2.8\%$ (minimum -7.9%, maximum 21.6%) and $1.7 \pm 1.3\%$ (minimum -9.5%, maximum 21.5%) for Figure 5(a), (b) and (c), respectively. For all these three cases, 97% of the projected breast area shows differences equal to or less than

10%, which was set as the maximum difference permitted (detailed information is provided below).

Figure 5: Relative error map, $\epsilon_S(x,y)$, for several simulated breast models for 0 degree projection angles: (a) $T = 3$ cm, $R = 4$ cm and $G = 35\%$; (b) $T = 6$ cm, $R = 8$ cm and $G = 17\%$ and (c) $T = 9$ cm, $R = 12$ cm and $G = 9\%$. Breast edge is highlighted with a solid black line.

After fixing T (6 cm), R (12 cm) and θ (0 degree), $\epsilon_S(x,y)$ for different glandularities (2, 17 and 40%) is shown in figure 6. The corresponding average and standard deviation moduli of the errors are $2.1 \pm 1.4\%$ (minimum -4.6%, maximum 23.3%), $1.9 \pm 1.4\%$ (minimum -8.1%, maximum 25.4%) and $3.5 \pm 2.8\%$ (minimum -15.2%, maximum 23.6%). The fractions of the projected breast with $\epsilon_S(x,y)$ below 10% are 100%, 100% and 97% respectively. The values of $\epsilon_S(x,y)$ observed within the projected breast area are below 5% (cyan and green) in the central area of the breast.

Figure 6: Relative error maps $\epsilon_S(x,y)$ for a phantom with $T = 6$ cm, $R = 12$ cm and $\theta = 0$ degrees. Glandularities correspond to (a) 2, (b) 17 and (c) 40%. Breast edge is highlighted with a solid black line.

Figure 7 depicts, for a given phantom ($T = 6$ cm, $R = 8$ cm, $G = 17\%$), the variations

of $\epsilon_S(x,y)$ with projection angle (0, 7.5 and 25 degrees). As expected, the projected breast is shifted towards the left edge of the image as the x-ray source is moved towards the right side, as does the ROI as presented in Figure 3(b). Average and standard deviation modulus values within projected breast area are $2.7 \pm 2.8\%$ (minimum -7.9%, maximum 21.6%), $2.8 \pm 2.7\%$ (minimum -6.2%, maximum 21.2%) and $2.9 \pm 2.6\%$ (minimum -8.0%, maximum 25.5%) for 0, 7.5 and 25 degrees, respectively. For these cases, 99% of the breast area has differences from the ground truth data equal to or below 10%.

Figure 7: Relative error maps $\epsilon_S(x,y)$ for a 6 cm thick and $R = 8$ cm breast phantom ($G=17\%$) at (a) 0, (b) 7.5 and (c) 25 degrees' projection angles. Breast edge is highlighted with a solid black line.

III.B. Scattered radiation for different glandularity patterns

As previously described, for the phantom ($T = 6$ cm, $R = 12$ cm, $G = 17\%$), three different fibroglandular distribution patterns were produced (Figure 2). Figure 8 shows $\epsilon_S(x,y)$ for this phantom, and a 0 degrees projection. The mean and standard deviation modulus errors observed within the projected breast area are $3.4 \pm 2.6\%$ (minimum -13.3%, maximum 17.0%), $2.6 \pm 1.8\%$ (minimum -11.2%, maximum 27.7%) and $2.4 \pm 1.9\%$ (minimum -11.6%, maximum 22.3%), for each of the cases shown. 99% of the projected breast areas have $\epsilon_S(x,y)$ below 10%.

Figure 8: Relative error maps $\epsilon_S(x,y)$ for a 6 cm thick and 12 cm radius phantom ($G = 17\%$, $\theta = 0$ degrees), and different fibroglandular pattern distributions (P1, P2, P3). Breast edge is highlighted with a solid black line.

III.C. Scattered radiation using other breast models

Differences between the estimated and ground truth scattered radiation, i.e. $\epsilon_S(x,y)$, are shown in Figure 9 for the 5 cm thick compressed UPenn breast model ($G = 20\%$) and the 6 cm thick compressed Duke University breast phantom ($G = 32\%$). The average and standard deviation of the modulus error are $1.7 \pm 1.3\%$ (minimum -7.8% , maximum 8.0%) and $5.1 \pm 2.9\%$ (minimum -15.3% , maximum 7.4%) for the UPenn and Duke phantoms, respectively, at $\theta = 0$ degrees. 97% of area of the UPenn projected images show differences below 5% for all simulated projection angles, whereas 93% of the areas of Duke phantom projected images show differences up to 10%.

Figure 9: $\epsilon_S(x,y)$ using (a) 5 cm thick UPenn breast model ($G = 20\%$) and (b) 6cm thick Duke University breast model ($G = 32\%$), acquired at $\theta = 0$ degrees. Breast edge is highlighted with a solid black line.

The results for all simulations are illustrated in Table 2. Modular average and standard deviation, and minimum and maximum values of ϵ_S for all pixels within the projected breast area of are shown. Additionally, the fractions of the breast area within several percentage errors ($\epsilon_S \leq 2\%$, 5% 10% , 12% and 15%) are given.

Table 2: Error analysis for each phantom and acquired geometry.

Phantom	T (cm)	R (cm)	G (%)	θ (degrees)	Mean ϵ_S (%)	Stdev. ϵ_S (%)	Min. ϵ_S (%)	Max. ϵ_S (%)	$\epsilon_S \leq 2\%$ (%)	$\epsilon_S \leq 5\%$ (%)	$\epsilon_S \leq 10\%$ (%)	$\epsilon_S \leq 12\%$ (%)	$\epsilon_S \leq 15\%$ (%)
Elangovan et al ³³	3	4	35	0	1.6	1.3	-5.9	19.3	68.8	98.3	99.9	99.9	100.0
				7.5	1.6	1.3	-5.8	18.3	70.7	98.0	99.8	99.9	99.9
				25	1.7	1.4	-5.8	20.8	65.9	97.9	99.9	99.9	100.0
		8	35	0	2.1	1.7	-7.4	13.1	57.5	93.8	99.9	100.0	100.0
				7.5	2.0	1.7	-7.8	16.2	58.6	93.7	99.8	100.0	100.0
				25	2.2	1.9	-7.7	16.3	58.3	90.9	99.8	100.0	100.0
		6	8	17	0	2.7	2.8	-7.9	21.6	54.2	84.1	96.6	98.9
					7.5	2.8	2.7	-6.2	21.2	52.5	83.2	97.1	98.8
					25	2.9	2.6	-8.0	25.5	47.2	80.5	98.1	99.3
			2	0	2.1	1.4	-4.6	23.3	52.9	96.5	100.0	100.0	100.0
					7.5	1.9	1.4	-4.2	26.1	58.2	97.2	100.0	100.0
					25	1.8	1.3	-7.3	11.8	63.7	97.6	100.0	100.0
			17	0	1.9	1.4	-8.1	25.4	60.4	97.1	100.0	100.0	100.0
					7.5	1.9	1.4	-9.7	23.0	61.1	97.2	100.0	100.0
					25	1.9	1.5	-9.0	10.3	59.3	96.1	100.0	100.0
			17 (P1)	0	3.4	2.6	-13.3	17.0	37.4	73.6	98.5	99.9	100.0
					7.5	3.6	2.7	-14.0	16.5	34.6	70.7	98.2	99.9
					25	4.6	3.0	-17.0	4.8	22.5	59.8	94.9	98.8
			17 (P2)	0	2.6	1.8	-11.2	27.7	45.0	89.1	100.0	100.0	100.0
					7.5	2.4	1.8	-11.2	24.1	48.7	89.8	99.9	100.0
					25	2.8	2.2	-13.6	10.5	45.0	83.7	99.3	100.0
			17 (P3)	0	2.4	1.9	-11.6	22.3	51.6	89.7	99.9	100.0	100.0
					7.5	2.4	1.9	-10.9	23.4	52.3	89.3	99.9	100.0
					25	2.8	2.1	-13.3	10.2	44.4	85.2	99.6	100.0
			40	0	3.5	2.8	-15.2	23.6	38.7	73.6	96.8	99.4	100.0
					7.5	3.2	2.5	-14.2	22.8	40.8	77.9	98.6	99.8
					25	5.2	3.2	-16.5	5.5	16.2	53.0	91.5	96.6
	9	12	9	0	1.7	1.3	-9.5	21.5	63.4	98.4	100.0	100.0	100.0
				7.5	1.7	1.3	-7.5	24.6	64.9	98.5	100.0	100.0	100.0
				25	1.7	1.3	-9.0	12.1	65.5	97.9	100.0	100.0	100.0
		16	9	0	1.7	1.3	-7.0	10.4	65.3	98.2	100.0	100.0	100.0
				7.5	1.5	1.2	-11.0	9.8	70.3	98.7	100.0	100.0	100.0
				25	1.6	1.2	-10.0	10.7	68.2	98.4	100.0	100.0	100.0
		5	20	0	1.7	1.3	-7.8	8.0	63.1	98.4	100.0	100.0	100.0
				7.5	1.7	1.3	-7.4	6.6	64.8	98.2	100.0	100.0	100.0
				25	1.8	1.4	-8.7	7.3	61.3	97.2	100.0	100.0	100.0
Bakic et al ³⁴	5	5	20	0	5.1	2.9	-15.3	7.4	16.0	52.0	94.1	98.7	100.0
Li et al ³⁵	6	9	32	0	5.2	3.0	-16.2	7.4	15.5	50.2	92.6	98.3	100.0
				7.5	5.0	3.1	-15.2	6.5	20.0	54.0	93.0	98.7	100.0
				25	5.0	3.1	-15.2	6.5	20.0	54.0	93.0	98.7	100.0

IV. Discussion

As observed in Figure 4, the use of the ROI produces a normalised scatter signal of approximately 1 across the central region of the projected breast. As expected, this quantity increases towards the edges of the breast due to scattered radiation from the compression

paddle and breast support. This effect is also observed when the projection angle is increased, even though the scatter signal distribution is no longer symmetric (Figure 4(c)). Scattered radiation originating in parts of the DBT system (e.g. compression paddle and breast support table) is considered in this work. However, the photons scattered from the patient's body reaching the detector are not taken into account. Although several works having simulated a patient's body for scatter estimation^{11,40}, the magnitude of this scatter contribution was not discussed. We believe that the majority of scattered photons from the body will be mainly absorbed by the breast and little signal will reach the image receptor. They will probably represent a small fraction of the total scattered radiation, compared to that from the breast and compression paddle, however further investigation is needed to confirm this.

Through Figures 5 to 8, we have demonstrated that the proposed work can accurately estimate scatter fields for different T, G and θ , showing average modular differences below 5.2% for all simulated breast models (Table 2). Figure 7 shows how the errors in the left side of the periphery of the breast (yellow region) increase as the x-ray source is moved towards the right side of the figure. As described in the literature¹², this overestimation in scattered radiation is due to the increase of the airgap distance traversed by the x-ray photons between the bottom surface of the breast and the breast support, which is not properly modelled. Likewise, the UPenn and Duke breast phantoms (Figures 9) have shown average errors below 5.2%. The errors are mostly within 5% (green or cyan) in the central area, where the ROI is selected. Therefore, this supports the ascertainment that scattered radiation from homogeneous breast models can be used to approximate scatter field produced from heterogeneous models³². The largest discrepancies were found for the highest density (G = 40%), as observed in figure 6. However, this level of glandularity is rarely seen in routine breast screening, but may be pertinent in cases where younger women with a known history of breast disease are subject to mammography. This particular breast model shows larger differences (10-15%) near the edges of the breast, where there is more scattered radiation

from the compression paddle. To compute the scatter signal, the proposed method takes the SPR reference value in the center of the homogeneous phantom and this will differ largely from the SPR value of the peripheral area, as previously noticed in the literature where differences up to 30% in SPR were observed for DBT geometries¹¹. These low differences will be more relevant for larger breast densities. However, if using a VCT based on an M alternative forced choice (M-AFC) experiments, image patches from areas close to the edge of the breast might not be important to assess the imaging performance of a system. In addition, the amount of scatter from the compression paddle depends on its thickness and composition, and will thus differ between manufacturers.

Since the scatter field depends on the breast shape and composition, new phantoms will require running new Monte Carlo simulations. The use of low-resolution phantoms can reduce the computational time more than 40% with respect to that for high-resolution phantoms, while maintaining accuracy. However, given a fixed breast phantom size and glandularity, the same pre-calculated Monte Carlo results can be used for a wide range of distributions of fibroglandular tissue without the need for repeat simulations (Figure 8). It has been demonstrated that this scatter field estimation method works for three different types of breast models. The breast models used in this study have a compressed shape which varies slowly for the different configurations, thus new combinations could be obtained by interpolating the pre-calculated data for selected T, G and θ .

Note that, as commented earlier, only errors within the breast area were computed because the background does not have clinical relevance. Since automated segmentation was used to define the outline of the projected breast, slightly unrealistic breast edges might have been used to estimate $\epsilon_S(x,y)$ for the largest projected breasts (Figure 7(c)).

For all the phantoms simulated, the average SPR values within the ROIs range between 0.3 and 1.4. Therefore our target 10% error in scatter signal represents an error in the total simulated image ($P + S$) below 6%. We have demonstrated that our method estimates

scattered radiation with a 5% error within 87% of the projected breast area, on average. Therefore our approach for VCT schemes allows the rapid estimation of scatter fields in less than 20 seconds with errors of 3% within most of the area of the synthetic ($P + S$) image. By contrast we note that in certain VCT schemes scattered radiation is sometimes ignored^{49,50}.

Similarly, a recent VCT scheme²⁴ has shown fast generation of synthetic breast images, including scattered radiation. The average time to generate images for one patient was 8 central processing unit hours and 0.5 graphic processing unit hours, thus requiring good computer resources. By contrast, our approach could be run using a simple laptop since pre-calculated Monte Carlo simulations are used.

In addition, our method has potential to be applied in clinical DBT, although since it relies on the geometry of mathematical breast models, its accuracy as a scatter field reduction tool needs to be further tested.

V. Conclusions

A fast and simple method has been developed to estimate the 2D distribution of scattered radiation in VCT schemes which simulate DBT. A considerable reduction in the computational time has been shown with respect to other approaches^{12,27}. The proposed method, which uses pre-calculated Monte Carlo data using low-resolution breast models, takes less than 20 seconds to estimate the scatter field across the projected breast.

For the range of breast phantoms used in this study, the differences between the proposed scatter field estimation method and the ground truth data (direct Monte Carlo with high resolution anthropomorphic phantoms) are on average below 5.2% (minimum -17.0%, maximum 27.7%) within the projected breast area. It was found that, on average, the scatter field estimation method can estimate scattered radiation with an error of 10% (or less) in

99% of the projected phantom area. If the accuracy requirement is set to 5% differences in scatter signal, 87% of all analysed cases are below this threshold. Thus, the method, which has been validated using three of the most commonly used breast models in the field, is a useful tool to accurately insert scattered radiation into VCT schemes.

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Conflict of Interest

The authors have no relevant conflicts of interest to disclose.

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Fig. 1: Schematic diagram of the geometry used in the Monte Carlo simulations in (a) sagittal and (b) coronal view. The detector tilts with projection angles. Note that the figures are not in scale.

Fig. 2: (a-c) Central slices of 6 cm thick compressed voxelised breast phantoms, 12 cm radius and volumetric glandularity 17% using different patterns (P1-P3). The corresponding homogeneous breast model is shown in (d). Note that the homogeneous breast has a lower resolution. Sample slices of breast models developed at UPenn³⁴ and Duke University³⁵ are depicted in (e) and (d), respectively. The different tissues has been indicated: Skin, fibroglandular tissue (FT), adipose tissue (AT), Cooper's ligaments (CL), blood vessels (BL) and adipose cavities (AC).

Fig. 3: (a) Projected breast contours and corresponding ROIs for projection angles of 0 and 25 degrees are illustrated in green and red, respectively. (b) Normalised scatter map, $S'_{hom}(x, y)$, for an homogeneous phantom (T = 6 cm; R = 8 cm; G = 17%) at $\theta = 0$ degrees. The contour of the projected breast is shown in green and the white lines correspond to the location of intensity profiles shown below.

Fig. 4: Horizontal (first column) and vertical (second column) intensity profiles of $S'_{hom}(x, y)$ as illustrated in Figure 3(b). First and second rows correspond to a phantom of T = 6 cm, R = 12 cm and different glandularities (2, 17 and 40%) simulated at $\theta = 0$ and $\theta = 25$ degrees, respectively. Bottom row (e-f) represents phantoms of R = 12 cm and thickness of 6 cm (G = 17%) and 9 cm (G = 9%) for $\theta = 0$ degrees. Vertical dashed lines represent the projected edge or boundary of the phantom.

Fig. 5: Relative error map, $\epsilon_S(x, y)$, for several simulated breast models for 0 degree projection angles: (a) T = 3 cm, R = 4 cm and G = 35%; (b) T = 6 cm, R = 8 cm and G = 17% and (c) T = 9 cm, R = 12 cm and G = 9%. Breast edge is highlighted with a solid black

line.

Fig. 6: Relative error maps $\epsilon_S(x,y)$ for a phantom with $T = 6$ cm, $R = 12$ cm and $\theta = 0$ degrees. Glandularities correspond to (a) 2, (b) 17 and (c) 40%. Breast edge is highlighted with a solid black line.

Fig. 7: Relative error maps $\epsilon_S(x,y)$ for a 6 cm thick and $R = 8$ cm breast phantom ($G=17\%$) at (a) 0, (b) 7.5 and (c) 25 degrees' projection angles. Breast edge is highlighted with a solid black line.

Fig. 8: Relative error maps $\epsilon_S(x,y)$ for a 6 cm thick and 12 cm radius phantom ($G = 17\%$, $\theta = 0$ degrees), and different fibroglandular pattern distributions (P1, P2, P3). Breast edge is highlighted with a solid black line.

Fig. 9: $\epsilon_S(x,y)$ using (a) 5 cm thick UPenn breast model ($G = 20\%$) and (b) 6cm thick Duke University breast model ($G = 32\%$), acquired at $\theta = 0$ degrees. Breast edge is highlighted with a solid black line.