Accurate local estimation of compressed breast thickness in digital breast tomosynthesis using an iterative reconstruction approach

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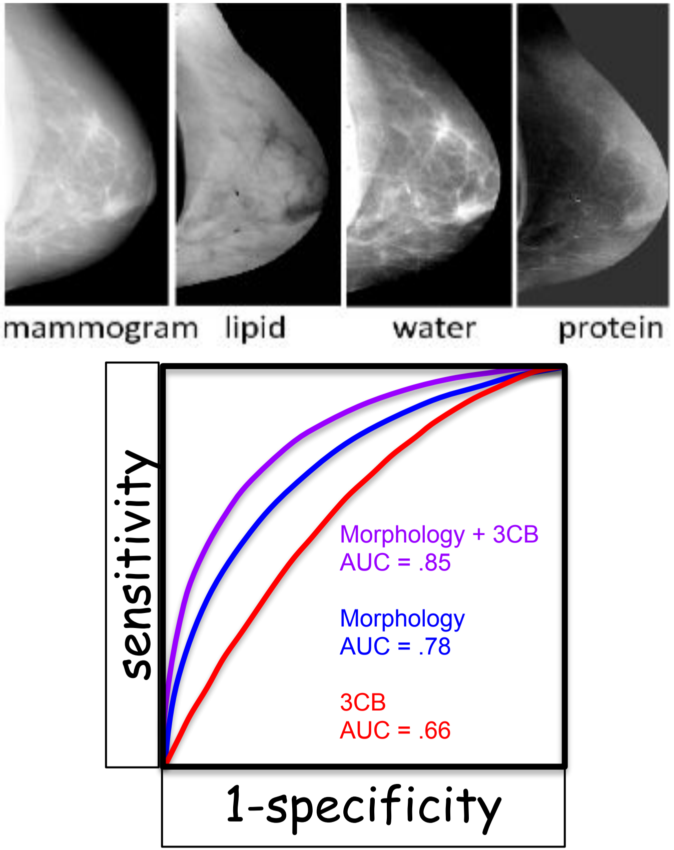
Importance of breast composition

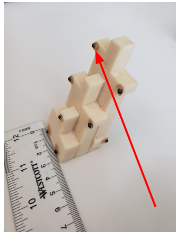
- Previous works investigated breast composition and how it relates to different lesion types
- Compositional features of breast lesions were shown to be diagnostically significant
- Three compartment brest or 3CB algorithm
  - Concept: Lipid, water, and protein are the three major components of breast tissue
  - Method: Uses dual energy mammography and thickness measurements to derive lipid, water, and protein maps for a given breast
  - Significance: Malignant lesion types have unique compositions when compared to non-malignant types.



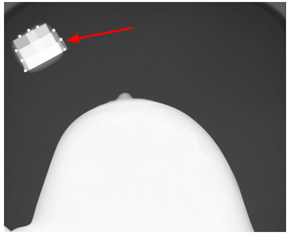
Drukker, Med Phys. 2014 Mar; 41(3): 031915.

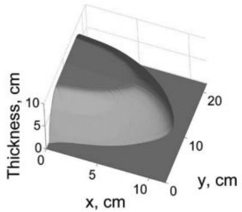
3CB for full field digital mammography (FFMD)

- Accurate thickness is vital input for the 3CB algorithm
- Prior 3CB work was developed for 2D
- Breast geometry and thickness was derived with the help of a phantom attached to the top of the compression paddle
  - The paddle phantom contains 9 lead bbs (indicated by red arrows)
  - Paddle tilt, warp, and compression is determined from the bbs spatial relation to each other
- Issues with using the paddle phantom:
  - Data needs to be collected prospectively with the phantom attached to the paddle
  - Requires extra setup and calibration


Paddle phantom


Orientation of phantom on compression paddle


Raw FFDM with paddle phantom



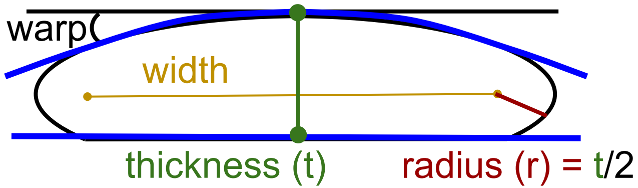
Calculated thickness map

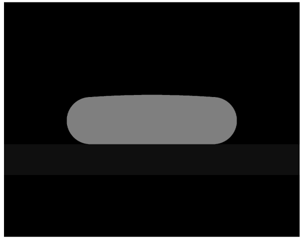
3 compartment breast for tomosynthesis

- **Goal**: Apply the 3CB methods and algorithm to tomosynthesis to create lipid, water, and protein volume fractions
- **Problem**: Tomosynthesis has poor resolution in the z-axis thus making it difficult to get accurate thickness measurements
- **Hypothesis**: Tomosynthesis images contain enough information from which thickness and other geometrical measurements can be derived using sinograms.

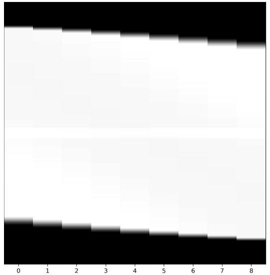
Approach with simulation

- We created a virtual breast object for which we can define the cross sectional geometry parameters of a compressed breast
    - Parameters: thickness, width, and warp
- We use Matlab simulation to create simulated sinograms from the virtual breast object we define
- Sinogram - A set of projections under different angles organized in 2D
    - GE’s system create 9 projections
    - Each pixel column, from the chest wall to the nipple, is a cross sectional slice and a sinogram can be generated for each

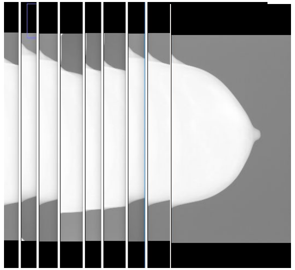




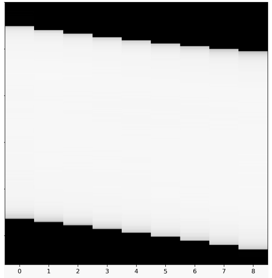
Virtual Breast Object



Simulated sinogram



9 projections



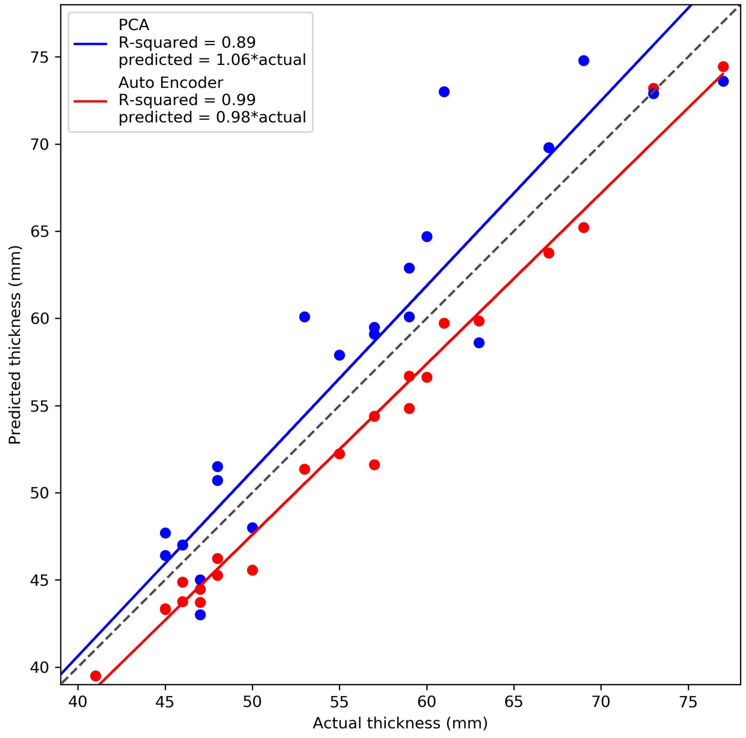
Real sinogram

Prediction and modeling approaches

- Method 1: Iterative reconstruction
  - Virtual breast object and its simulated sinogram was generated and compared to the real sinogram until error was minimized
  - Regenerating new breast objects of different parameters (width, thickness, and warp) and its sinograms to match the real sinogram was computationally expensive.
- Method 2: Machine learning
  - Sampled the search space of possible breast parameters to generate a training set of 13107 sinograms and a validation set of 3277 sinograms
    - width: .1 - 200 mm,
    - thickness: .1 - 80 mm,
    - warp: 0 - 4 degrees
  - <u>Models</u>:
    - Principal components analysis (PCA)
    - Auto encoder

Results for Method 2: PCA and auto encoder thickness predictions

- 24 real patients scans were evaluated by the PCA and auto encoder models to predict the thickness recorded in the DICOM header
  - Cranial Caudal (CC) view
  - Taken on General Electric's (GE) SenoClaire Tomosynthesis system
  - DICOM header field (0018, 110A) for body part thickness



Thickness estimation evaluation

- 24 patient scans were evaluated by both the PCA and auto encoder model
- Predictions were compared to the thickness reported in the DICOM header

	Mean DICOM Header Thickness (mm)	DICOM header - Predicted Mean (mm)	Standard Deviation (mm)	Minimum Difference (mm)	Maximum Difference (mm)	RMSE (mm)	R^2
PCA Thickness Estimate	53.76	-0.84	3.85	-5.10	5.40	3.86	0.89
Auto Encoder Thickness Estimate	53.76	2.67	0.90	1.12	4.16	2.56	0.99

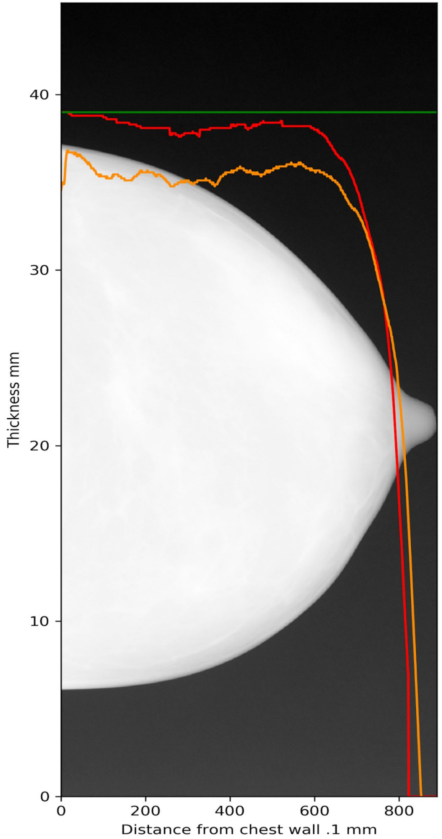
Full thickness estimates examples

- Final PCA and auto encoder models were used to predict all cross sectional slices from the chest wall to the nipple for a single patient

Green - Thickness recorded in the DICOM header

Orange - Thickness estimated via PCA

Red - Thickness estimated via auto encoder



Tilt and warp geometrical predictions

- Calculating tilt:
  - We assume that the breast is in contact with the compression paddle out to ⅔ distance from the chest wall.
  - We exclude 1 cm from the chest wall due to chest wall artifacts such as muscle and skin
  - A slope can be calculated by the change in thickness as we move away from the chest wall

	Units	Mean	Standard Deviation	Minimum	Maximum
Auto Encoder Warp Estimates	Degrees	0.11	0.04	0.08	0.23
Auto Encoder Tilt Estimates	Degrees	0.06	0.61	2.7 E-04	1.02

Concluding remarks

- We have demonstrated an ability to derive the geometrical parameters (thickness, width, warp, and tilt) of a compressed breast from its sinograms using an auto encoder
- With an accurate thickness model, we can work towards creating 3D lipid, water, and protein volumes of the breast
- We have shown how simulation and simulated data can be used to build translational models which can benefit from addition of real data downstream.

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