STRUCTURAL SIMILARITY INDEX ALGORITHM FOR ACCURATE MAMMOGRAM REGISTRATION

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Education

- **B.S. in Computer Engineering, 2006**

  University of Technology, Baghdad-Iraq

- **MSE in EE, 2012, a recipient of Fulbright Scholar**

  University of Alabama in Huntsville, Huntsville-Alabama

- **Ph.D. in EE, 2012-2015**

  University of Alabama in Huntsville, Huntsville-Alabama

Employment History

- **Engineer, 2007-2009**

  Ministry of Higher Education and Scientific Research, Baghdad-Iraq

- **Research/Teaching Assistant, 2009-2015**

  University of Alabama in Huntsville, Huntsville, Alabama

- **Assistant Professor, 2015**

  Utah Valley University, Orem, Utah

Acknowledgment

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  - Diagnostic Radiology, Breast Diagnostic Center
  - Huntsville, Alabama
- Dr. Heidi Umphrey, M.D.
  - Chief, Breast Imaging, Program Director Breast Imaging Fellowship, UAB
  - Associate Professor, Breast Imaging Section, UAB
  - Birmingham, Alabama

Outline

- Objective
- Breast Cancer Detection
  - Screening Mammography
  - Computer Aided Diagnosis
    - Pectoral Muscle Detection
    - Mammogram Registration
- Conclusion

Objective

Screening mammography often incorporates a computer aided diagnosis (CAD) scheme in its procedure to increase the accuracy of detecting gradual changes in breast tissues. One method for detecting gradual changes in temporal mammograms is through registration algorithms

Breast cancer Detection

- Mammography
  - Screening
    - 2-D
    - 3-D (Tomosynthesis)
  - Diagnostic
    - 2-D
    - 3-D (Tomosynthesis)
- Ultrasound
- Biopsy

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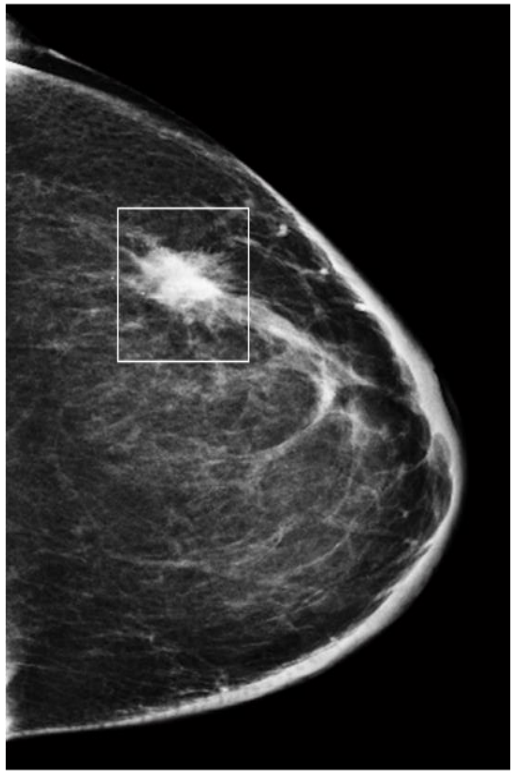
2-D Screening Mammography

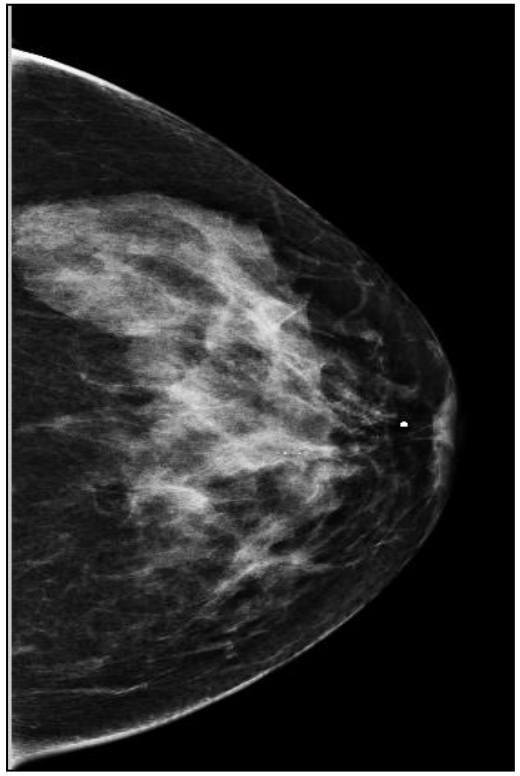
A low dose X-ray machine acquires mammogram images for the breast

http://www.123royaltyfree.com/photo_12860317_laboratory-with-mammography-machine.html

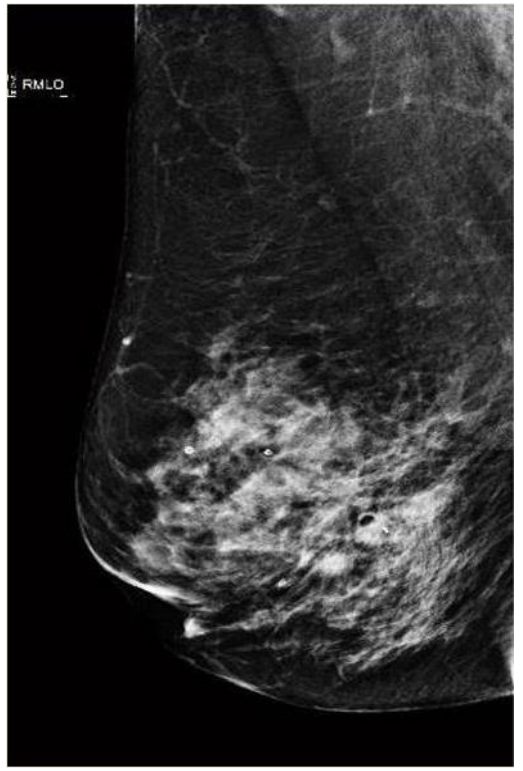
Mammographic Appearance of Breast Lesions



Mass

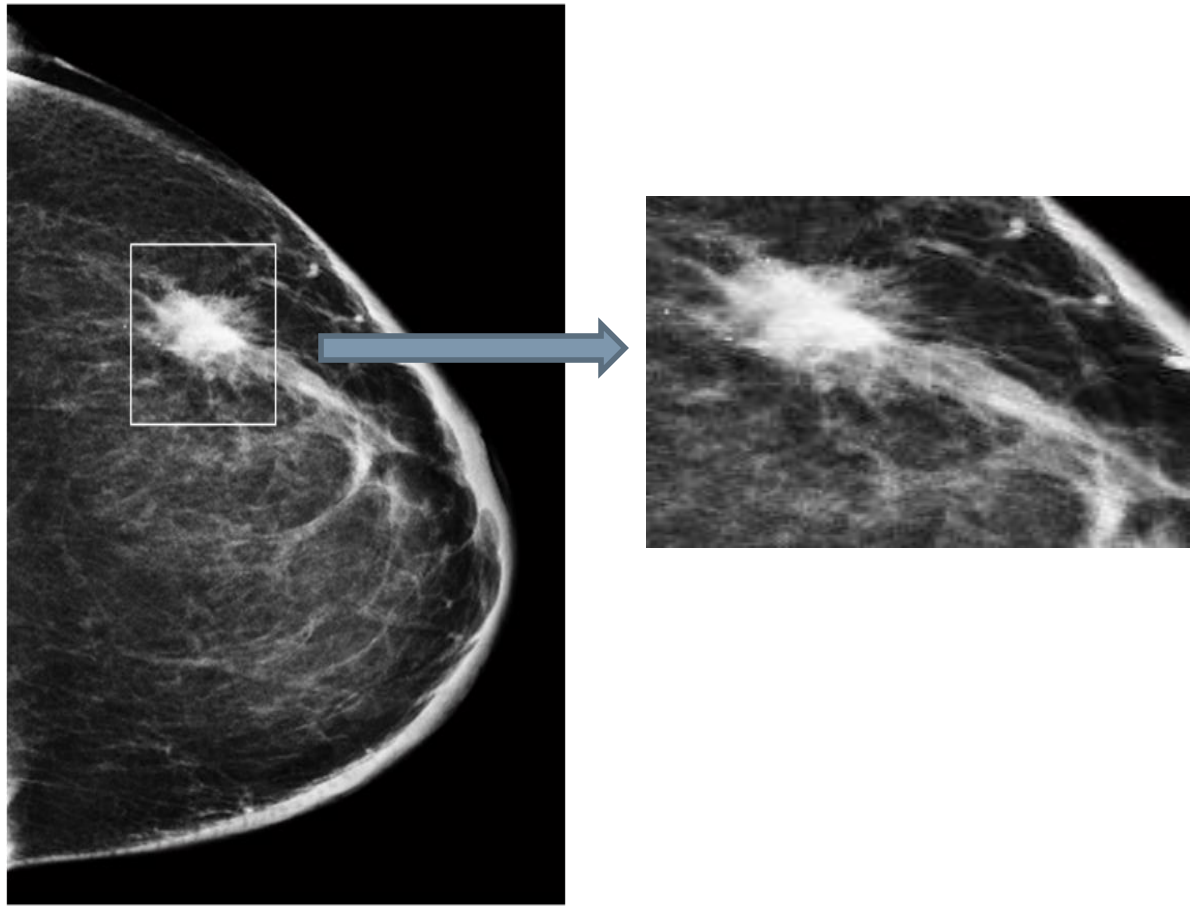


Calcifications



Architectural distortion

Masses



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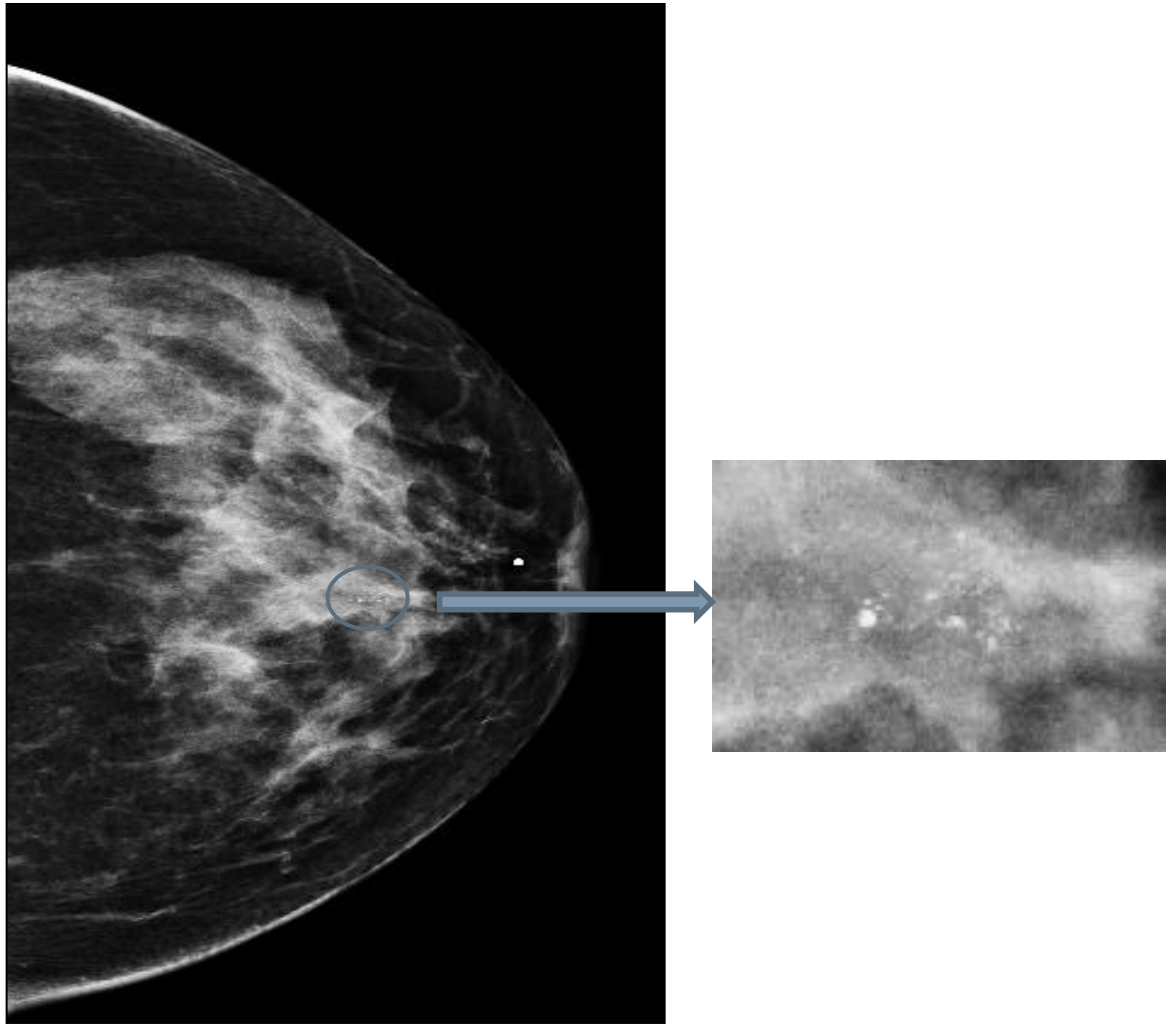
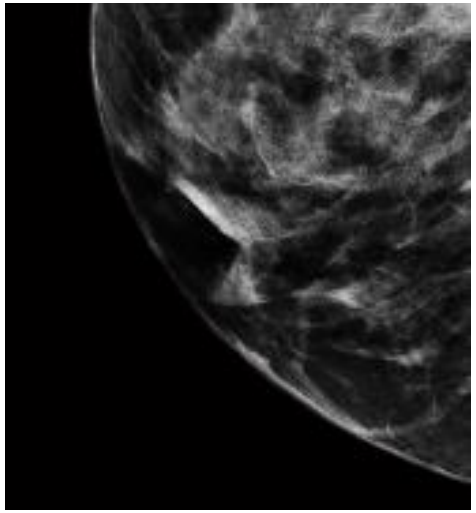
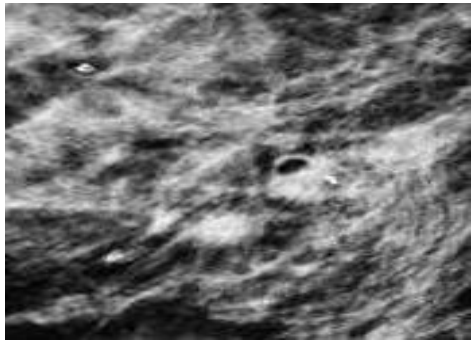


Architectural Distortions



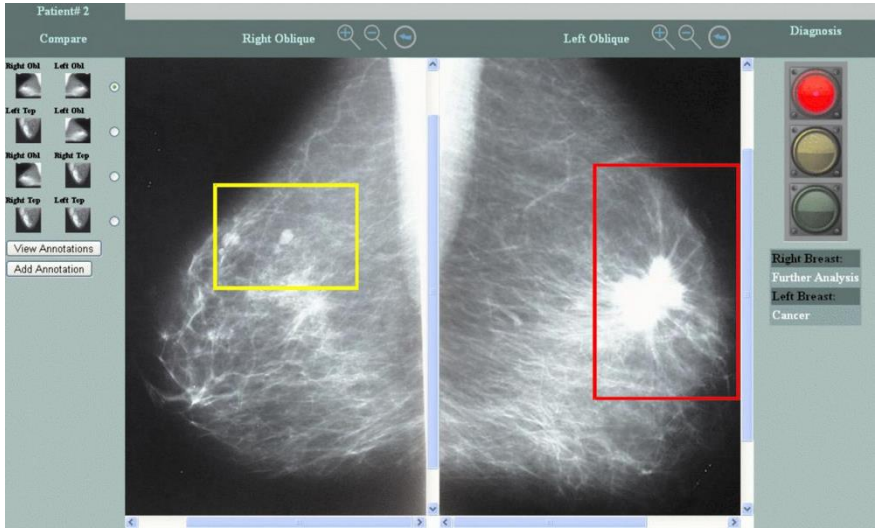
Nipple retraction



Spiculation radiating from a point

Computer-Aided Diagnosis (CAD)

- 10-30% of breast lesions are overlooked by radiologists
- Retrospective study
  - 48% of malignant cases signs were visible on prior mammograms
  - 9% of malignant cases were visible on screening mammograms obtained 2 years earlier



http://www.aicml.ca/?q=node/42

Computer-Aided Diagnosis (CAD)

- Developing an automated diagnostic and screening system that uses a fast computation environment for providing a second opinion
- Main goal
  - Improve the accuracy and consistency of mammogram interpretation by radiologists
  - Detect small gradual changes in breast tissue

CADs

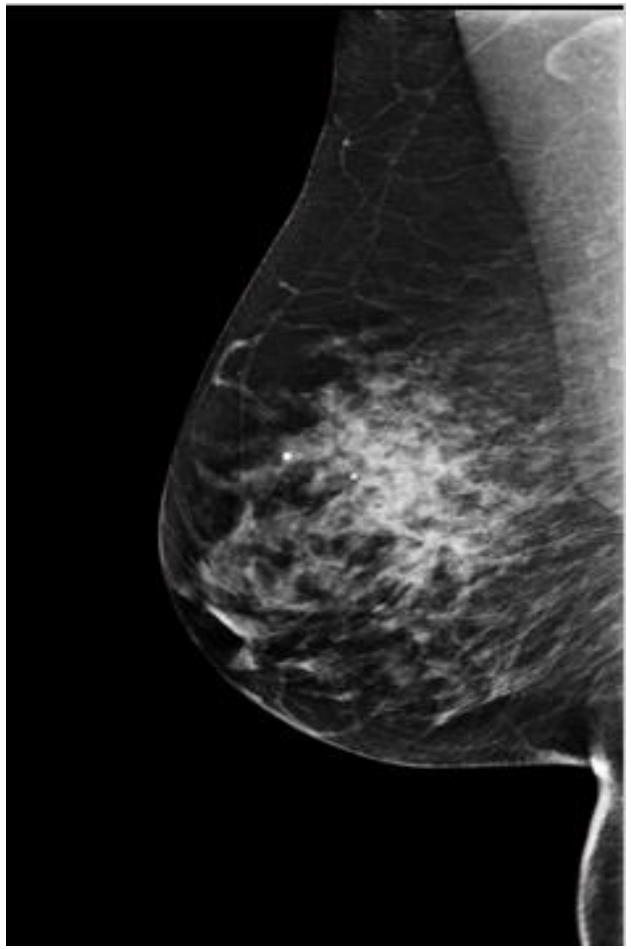
Available CADs

- work effectively in detecting masses and calcifications
- do not incorporate registration algorithm to map information in temporal mammograms
- incapable of detecting architectural distortion with a high level of accuracy

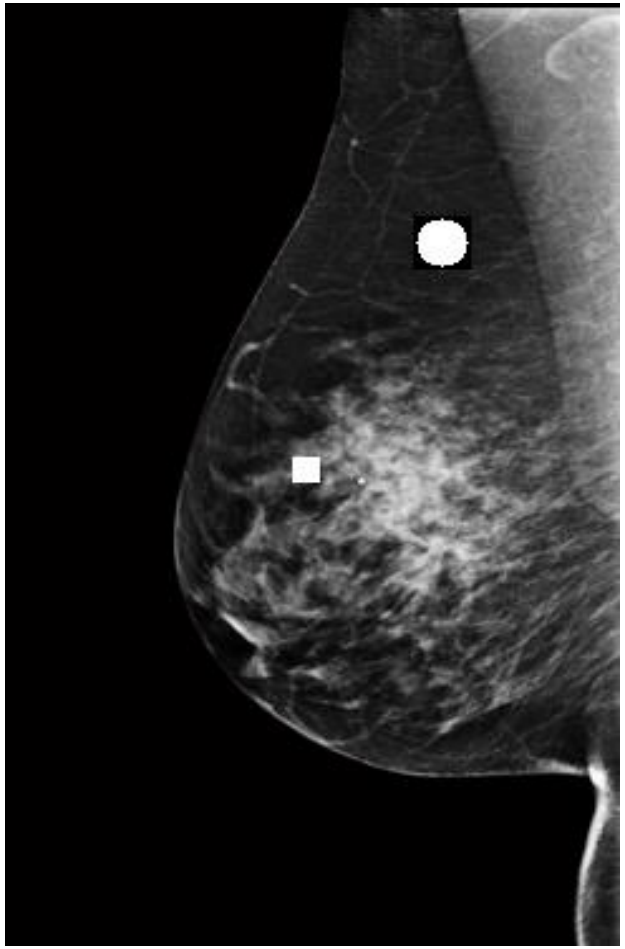
Mammogram Registration

Mammogram registration locates the differences in temporal mammograms to provide meaningful information to the radiologist for the purpose of early breast cancer detection

Ideal Registration

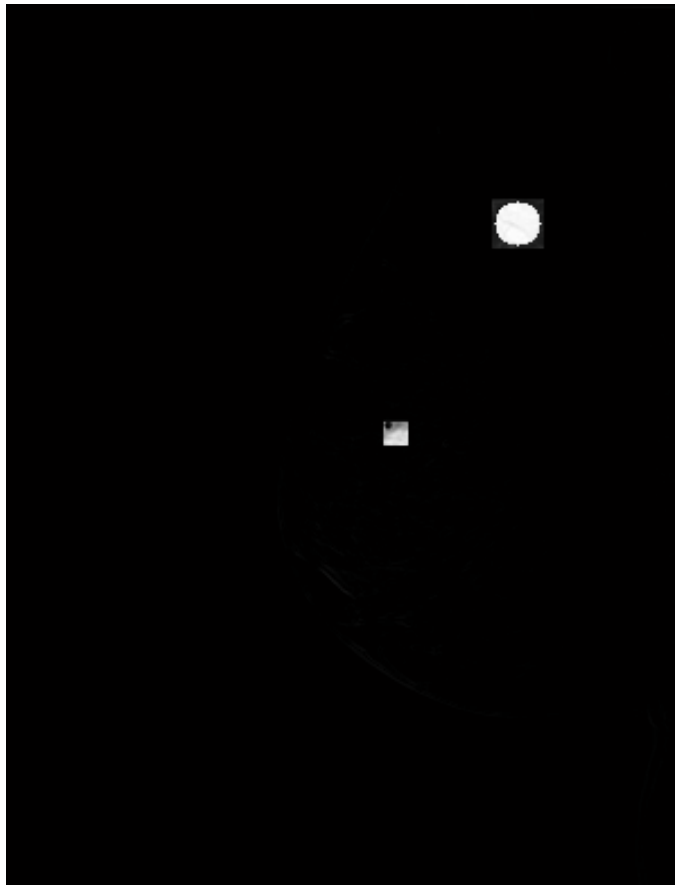


Reference mammogram



Target mammogram

Ideal Registration

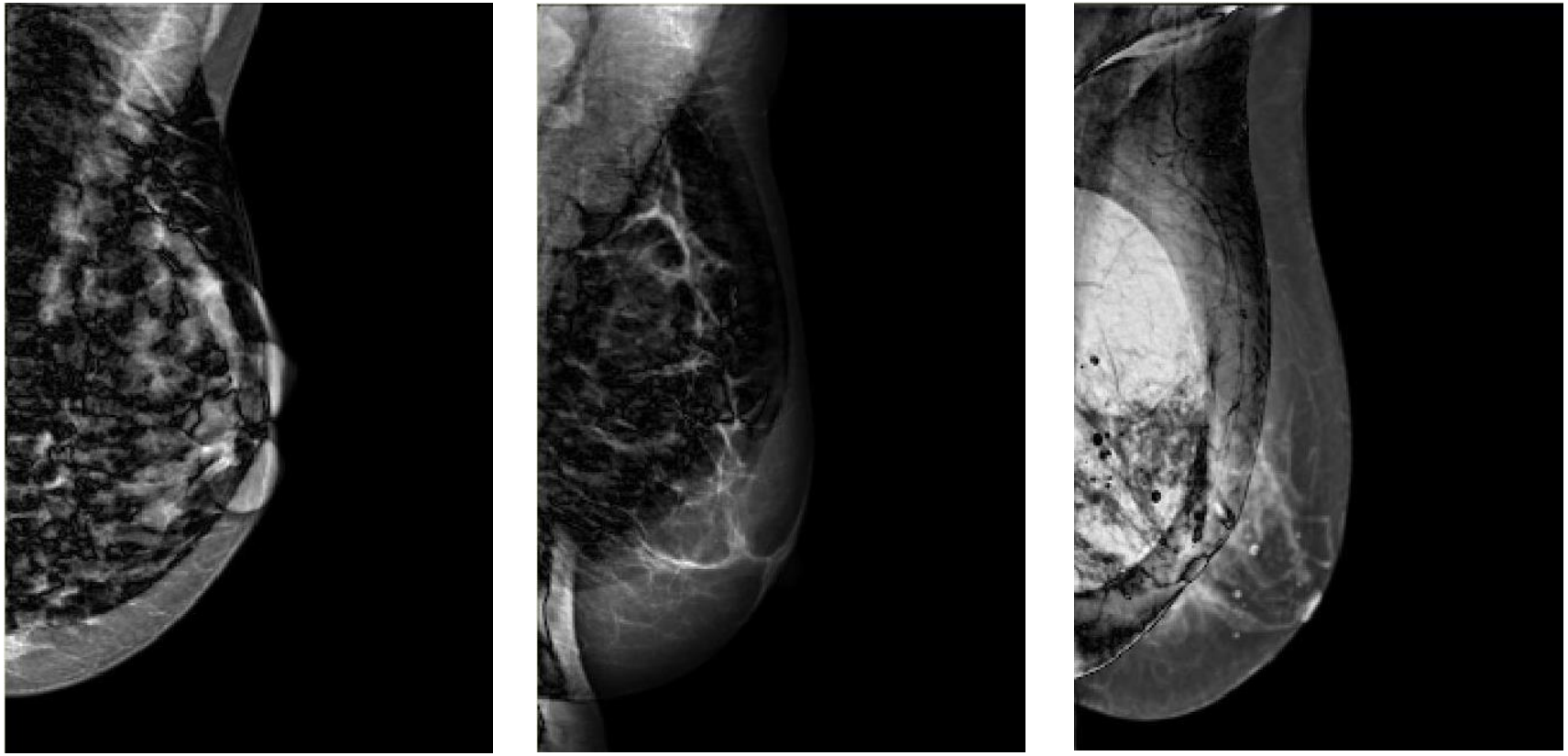


Registered mammogram pair
image difference

Challenges in Mammogram Registration

- Breast is a non-rigid object
- Variation
  - Compression
  - Imaging parameters
  - Shape
  - …

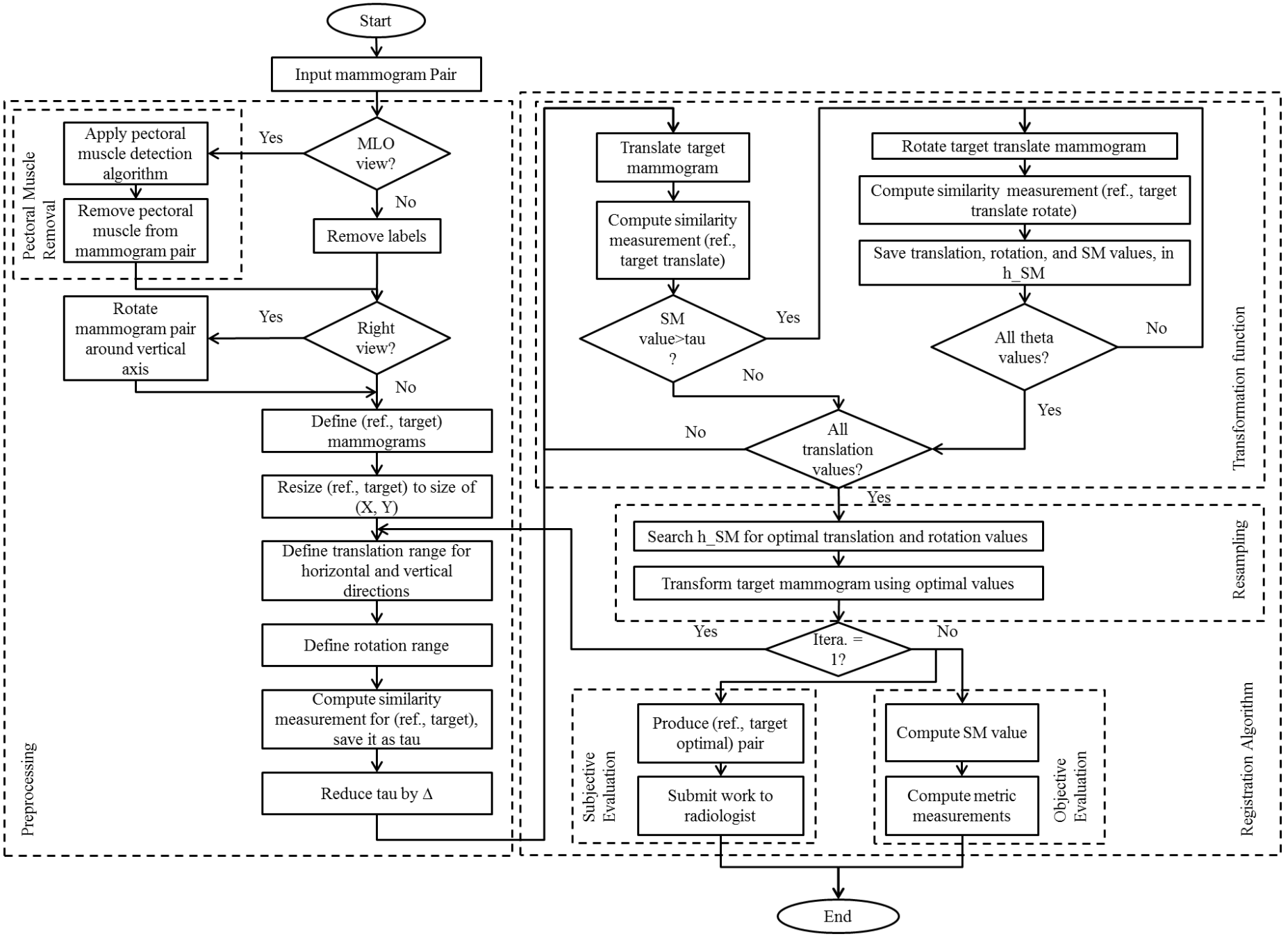
Challenges in Mammogram Registration



Registration Algorithm

- The pectoral muscle is removed from mammograms with mediolateral oblique (MLO) view and applied for a registration algorithm

- Registration Algorithm
  - Preprocessing
  - Transformation function
  - Resampling
  - Evaluation
    - Objective
    - Subjective


Start
Input mammogram Pair
Pectoral Muscle Removal
Apply pectoral muscle detection algorithm
Yes
MLO view?
No
Remove pectoral muscle from mammogram pair
Remove labels
Rotate mammogram pair around vertical axis
Yes
Right view?
No
Define (ref., target) mammograms
Resize (ref., target) to size of (X, Y)
Define translation range for horizontal and vertical directions
Define rotation range
Compute similarity measurement for (ref., target), save it as tau
Reduce tau by Δ
Preprocessing
Translate target mammogram
Compute similarity measurement (ref., target translate)
SM value>tau ?
Yes
No
Rotate target translate mammogram
Compute similarity measurement (ref., target translate rotate)
Save translation, rotation, and SM values, in h_SM
All theta values?
No
Yes
All translation values?
No
Yes
Transformation function
Search h_SM for optimal translation and rotation values
Transform target mammogram using optimal values
Resampling
Yes
Itera. = 1?
No
Produce (ref., target optimal) pair
Submit work to radiologist
Subjective Evaluation
Compute SM value
Compute metric measurements
Objective Evaluation
Registration Algorithm
End

Similarity Measurement

- structural similarity (SSIM) index is applied to compute the maximized similarity measurement between the registered mammogram pair
- The performance of SSIM is compared with mutual information (MI)

Objective Evaluation

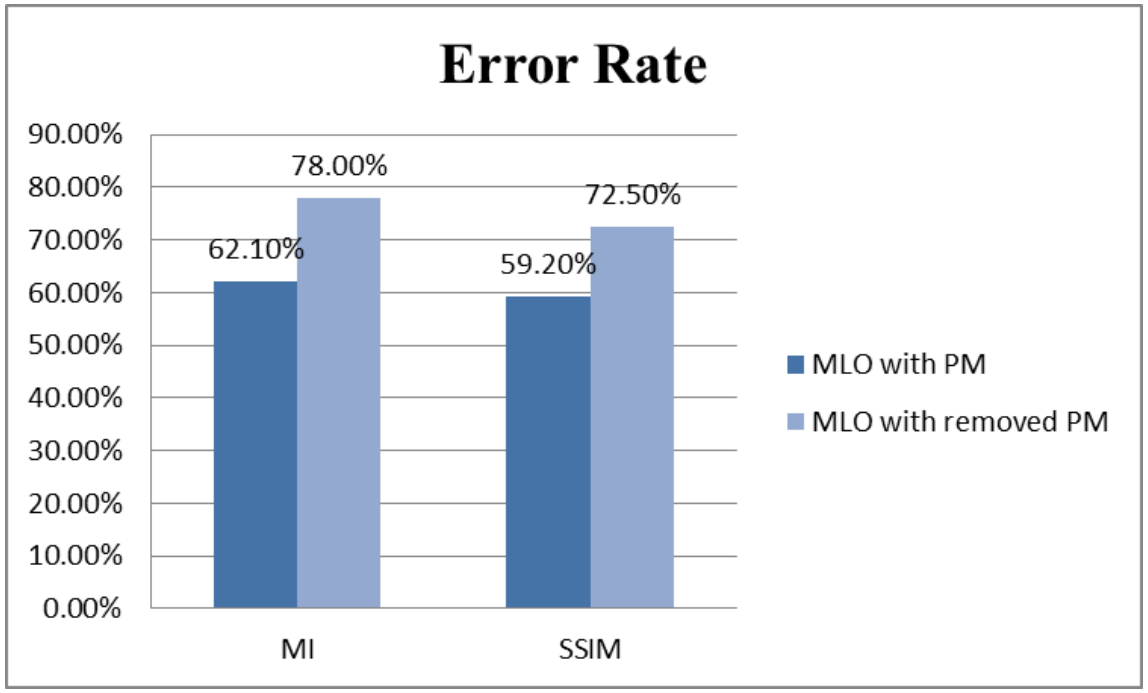
- The registration algorithm is applied on 45 of MLO view
- Objective evaluation

$$\text{Error\_ Rate} = \frac{\text{MSE\_Registration}}{\text{MSE\_Original}}$$

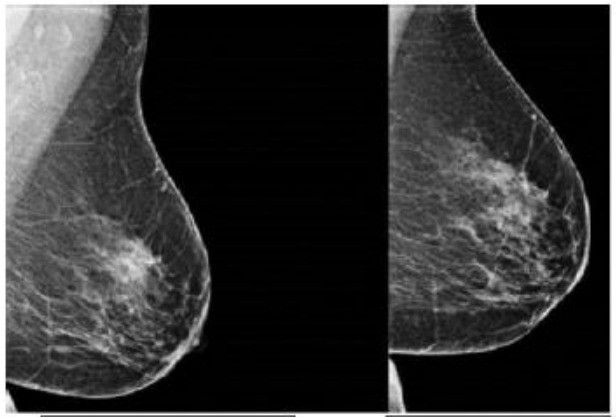
$$\text{MSE} = \sqrt{(\frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}(A(x,y) - B(x,y))^2)}$$

- Subjective evaluation
  - By experienced radiologist

Objective Evaluation

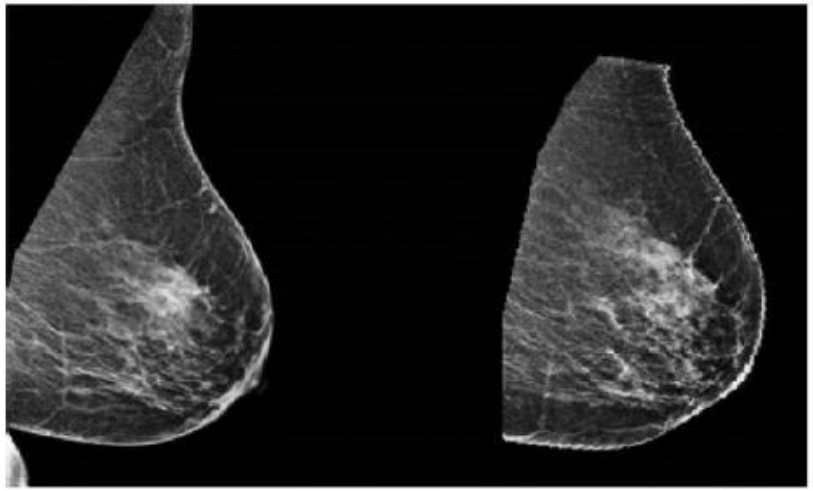


Subjective Evaluation by Radiologist



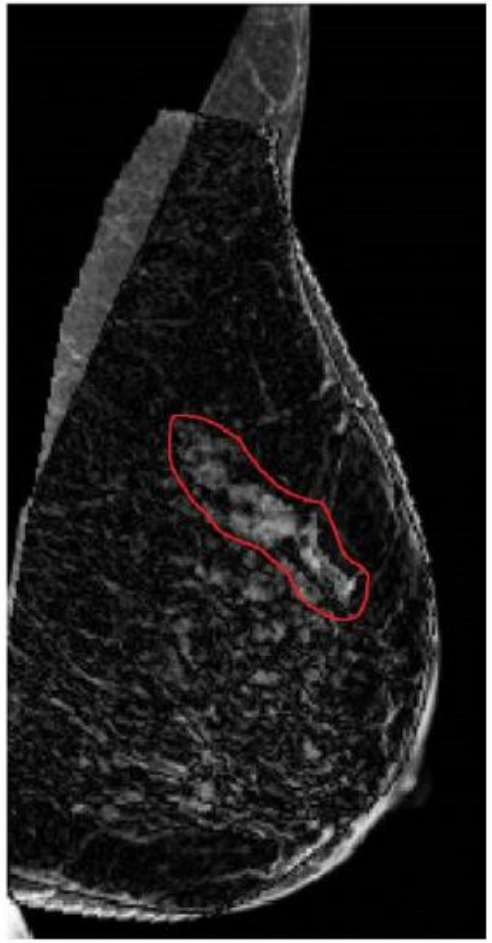
Reference mammogram

Target mammogram



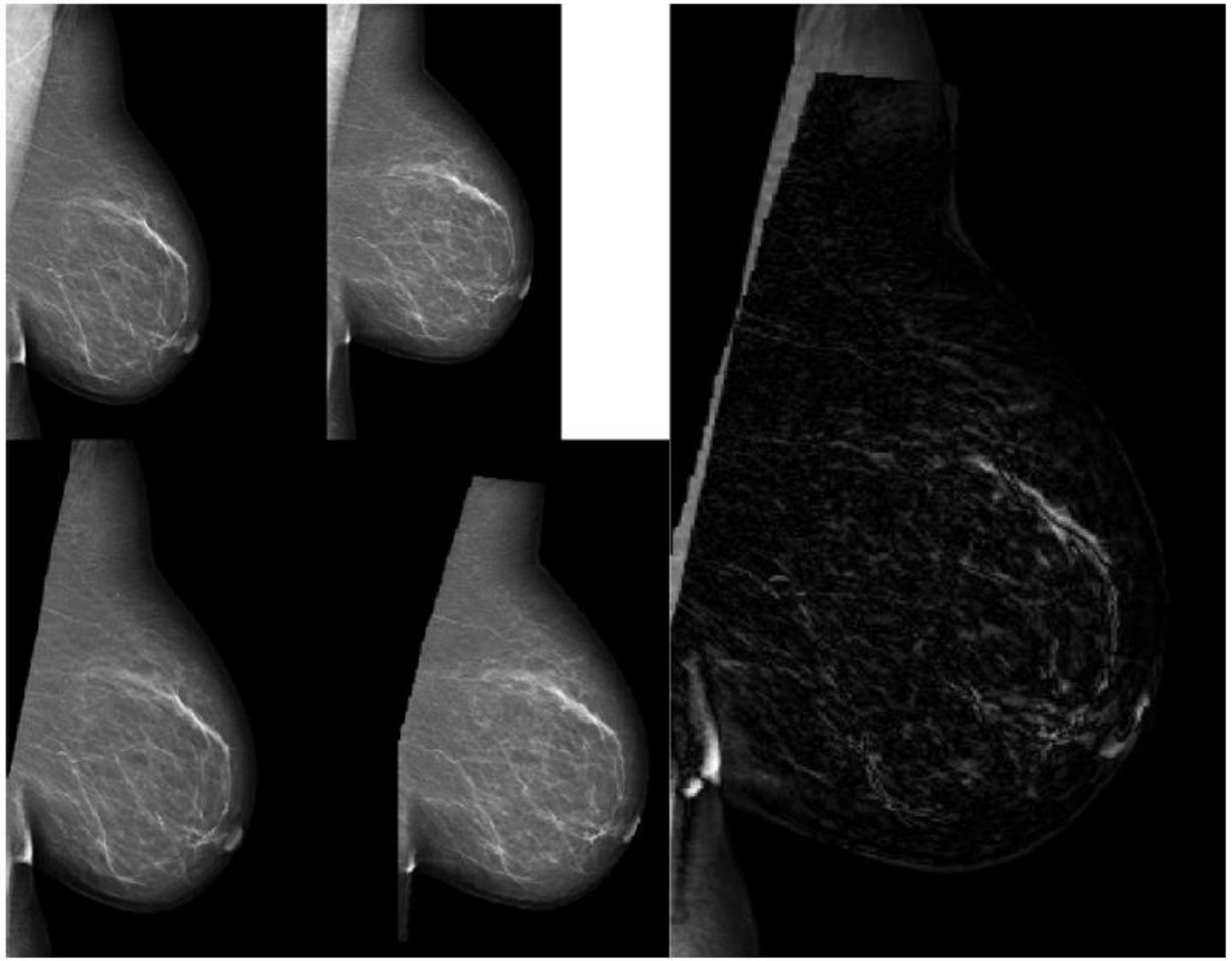
Reference mammogram

Transformed mammogram



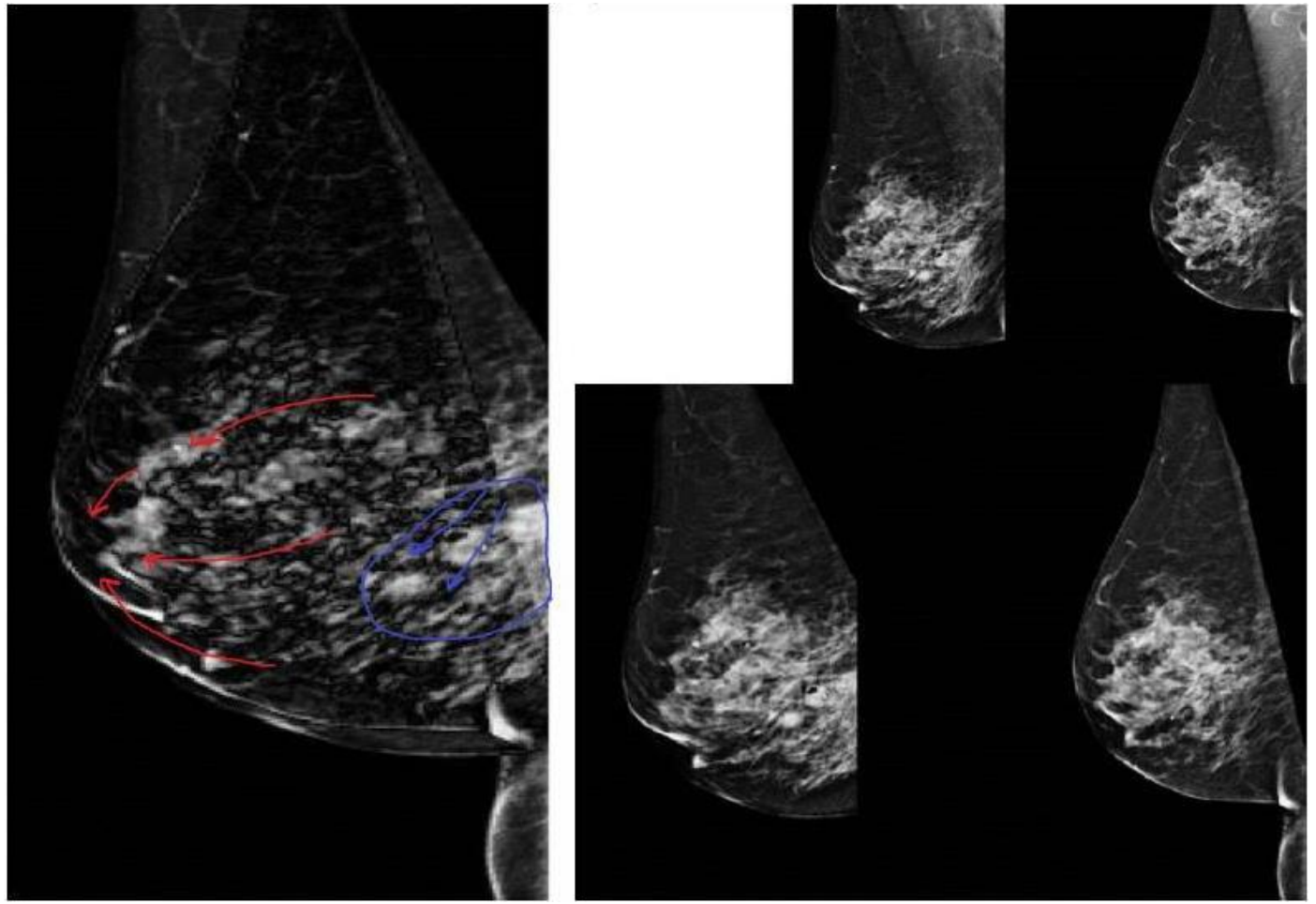
Superimposed reference and transformed mammograms

Subjective Evaluation by Radiologist



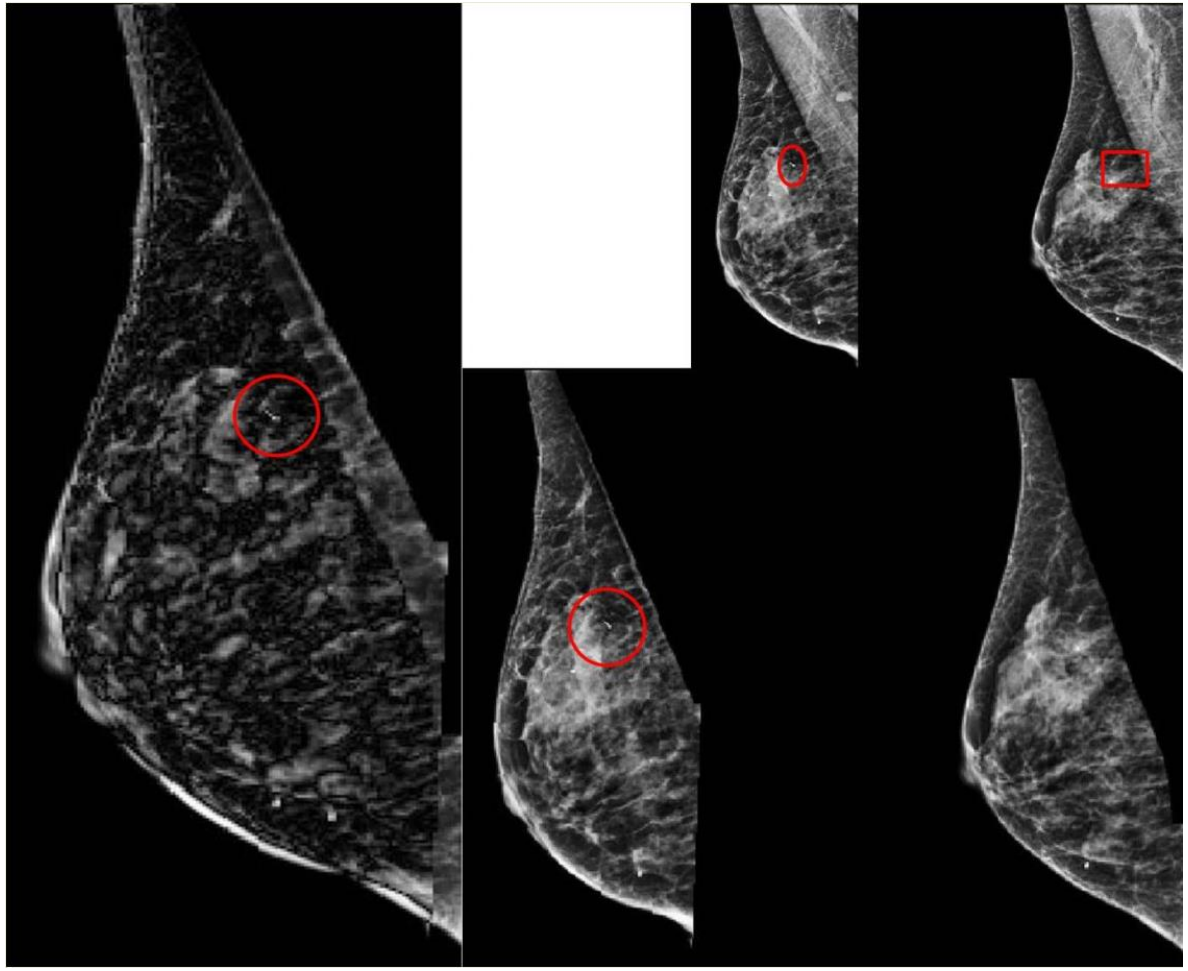
S1_1043, left breast

Subjective Evaluation by Radiologist



Diagnostic registration mammography, Case 49 and Case50, left breast

Subjective Evaluation by Radiologist



Case55, right breast

Subjective Evaluation by Radiologist

SSIM Performance	Count	Percentage
Better	16	35.56%
Same	21	46.66%
Worse	8	17.78%
Total	45	100%

Conclusion

- Mammogram registration
  - Reduced error rate when the pectoral muscle is removed
    - 72.50% to 59.20%
  - Applied SSIM and compare it with MI for MLO view with removed pectoral muscle, and MLO view with pectoral muscle, respectively
    - (59.40%, 72.50%) for SSIM
    - (64.30%, 78.00%) for MI

Publications

Journals and Magazines

- Huda Al-Ghaib, Melanie Scott, and Reza Adhami, **An Overview of Mammogram Analysis**. Accepted *in queue for publication*, IEEE Potentials Magazine, January 2015
- Huda Al-Ghaib, Yi Wang, and Reza Adhami, **A New Machine Learning Algorithm for Breast and Pectoral Muscle Segmentation**. European Journal of Advances in Engineering and Technology, Volume 2, Issue 1, Pages 21-29, January 2015
- Huda Al-Ghaib, Reza Adhami, and Yi Wang, **Margin Setting Algorithm for Mammogram Segmentation and Registration**. International Journal of Advances in Engineering and Technology, Volume 8, Issue 1, Pages 1927-1938, February 2015
- Yi Wang, Reza Adhami, Jian Fu, and Huda Al-Ghaib, **A Novel Supervised Learning Algorithm for Salt and Pepper Noise Reduction**. Springer International Journal of Machine Learning and Cybernetics, volume 6, Issue 4, Pages 687-697, August 2015
- Huda Al-Ghaib and Reza Adhami, **Digital Image Denoising with Edge Preservation**. Submitted to EURASIP Journal on Image and Video Processing, September 2015
- Huda Al-Ghaib and Reza Adhami, **Improved Denoising Process Based on Arbitrarily Shaped Windows**. Accepted, CSC International Journal of Image Processing(IJIP), October 2015

Publications

Conferences

- Huda Al-Ghaib, Reza Adhami, and Hai Dinh, **Improved Method of Pectoral Muscle Detection Based on Two Straight Line Fitting Algorithm**. IEEE International Conference on Industrial Automation and Information and Communications Technology (IAICT), pages 64-69, Bali, Indonesia, August 2014
- Huda Al-Ghaib and Reza Adhami, **On the Digital Image Additive White Gaussian Noise Estimation**. IEEE International Conference on Industrial Automation and Information and Communications Technology (IAICT), pages 90-96, Bali, Indonesia, August 2014
- H. Al-Ghaib and Reza Adhami, **Effect of AWGN Parameters Estimation on Accurate Denoising Process**. IEEE International Conference on Image Processing, Computer Vision, and Pattern Recognition (IPCV), Las Vegas, Nevada, July 2014
- John Miller, Huda Al-Ghaib, and Reza Adhami, **Minimal Haar Wavelet Transform for FPGA**. IEEE International Conference on Image Processing, Computer Vision, and Pattern Recognition (IPCV), Las Vegas, Nevada, July 2013
- Huda Al-Ghaib and Reza Adhami, **An E-learning Interactive Course for Teaching Digital Image Processing at The Undergraduate Level in Engineering**. IEEE International Conference on Interactive Collaborative Learning (ICL), Villach, pages 1-5, Austria, September 2012
- Huda Al-Ghaib, Reza Adhami, and Hai Dinh, **An Improved Image Compression Technique Based on Diagonal Edge Estimation**. Conference on Engineering and Technological Innovation (IMETI), Orlando, Florida, July 2012
- Jonathan Cross, Huda Alghaib, and Reza Adhami, **Eigenface Recognition Technique for ID Confirmation**. IEEE International Symposium on Information Theory (ISIT), Ica, Peru, November 2010

Questions