International Journal of Electronics and
Communication Engineering (IJECE)
ISSN(P): 2278-9901; ISSN(E): 2278-991X
Vol. 4, Issue 4, Jun- Jul 2015, 17-24

International Academy of Science, Engineering and Technology
Connecting Researchers; Nurturing Innovations

RADON TRANSFORM BASED CLASSIFICATION OF MAMMOGRAMS WITH IMPROVED LOCALIZATION

GOPAKUMAR C[1] & RAIBA RAHUMAN[2]

[1]Assistant Professor, Department of Electronics & Communication Engineering,
College of Engineering Karunagapally, India

[2]PG Scholar, Department of Electronics & Communication Engineering,
College of Engineering Karunagapally, India

ABSTRACT

This paper focuses on the development of a highly efficient computer aided detection system to classify normal and abnormal mammograms and to localize the calcification. The contrast enhancement of the image is done as a preprocessing step using contrast limited adaptive histogram equalization (CLAHE). Local maxima of the image is obtained using H-dome transformation. Extraction of features includes Discrete Cosine Transform (DCT) and Radon Transform (RT).The extracted features are given as the input to the SVM classifier. This algorithm tested on one hundred images and classified the normal and abnormal mammograms and finally reduced the region of interest by localizing the abnormalities like calcifications.

KEYWORDS: CLAHE, H-Dome Transformation, DCT, Radon Transform, SVM

I. INTRODUCTION

Cancer is a group of diseases involving abnormal cell growth with the potential to invade or spread to other parts of the body. In cancer, cells divide and grow without any control forming malignant tumors. Cancer spread to nearby parts and distant parts of body through blood and lymphatic system. Breast cancer is a type of malignant tumor that develops from breast cells. Glandular tissues and stromal (supporting) tissues are two main tissues in breast. Glandular tissues contains the milk-producing glands (lobules) and the ducts (the milk passages) while stromal tissues include fatty and fibrous connective tissues in the breast. Second leading cause of cancer death in women is breast cancer. It is the most common invasive cancer in females worldwide. It accounts for 16% of all female cancers and 22.9% of invasive cancers in women. 18.2% of all cancer deaths in both males and females worldwide, are from breast cancer.

Early detection of breast cancer has been known to improve recovery rates to a great extent. Mammography is one of the first diagnostic tests to prescreen breast cancer. The computer aided detection technology can help doctors and radiologists in getting a more reliable and effective diagnosis, since it checks the mammogram as the second reader. Both screen film and digital mammography are now available. In screen film mammography the images will be in black and white on a large sheet of film. In digital mammography images are directly recorded into a computer, It can then viewed on a computer screen and specific areas can be enlarged or highlighted. Mammography is used to detect a number of abnormalities, the two main ones being calcifications and masses. Calcifications are tiny mineral deposits within the breast tissue that appear as small white regions on the mammogram films.

The reminder of this paper is organized as follows. Section II briefly describes previous works. Section III describes the methodology. Section IV gives the simulation results and finally section V gives the conclusion.

II. RELATED WORKS

In [2], it uses multi-resolution analysis tool such as the discrete wavelet transform (DWT) for feature extraction. As the microcalcifications are high frequency component of the mammogram, detection of microcalcifications is achieved by decomposing the mammogram into different frequency sub bands, suppressing the low frequency sub band. The disadvantage is that wavelet transform often fails to accurately capture high frequency information especially at low bit rates.

In [3], it uses wavelet feature extraction, which improves sensitivity and performance of the detection of microcalcification in digital mammograms. Then it extract the gabor wavelet features. After extracting the features Principal Component Analysis (PCA) is used for dimensionality reduction.

In [4], Image divided into 8×8 pixel blocks and the five most significant coefficients of a 64-point DCT is determined by the fisher criterion, these coefficients were fed to a three-layer feed forward neural network with error back-propagation training (MLP-BP) to detect microcalcifications.

In [5], a 61- feature vector is formed to represent textural, spatial and spectral properties of small Region of Interset's. The spectral domain information consist of the block average and spectral entropy of a 16 × 16 DCT. The feature vectors were fed to both Support Vector Machines (SVM) and Generalized Regression Neural Networks (GRNN).

III. METHODOLOGY

The proposed method deals with a novel approach for the development of a highly efficient computer aided detection system to classify breast cancer images into normal and abnormal classes. The procedure for the proposed method consist of four main phases: preprocessing, feature extraction, classification, and localization of calcification.

A. Preprocessing

Aim of pre-processing is to improve the quality of mammogram for enhancing further processing [10]. Mammograms are either left or right. They are not oriented in the same direction and it contains some unwanted labels. In pre-processing, mammograms aligned into one direction using line detection method and omitting the unwanted symbols [6]. Mammogram contains pectoral muscles and are bright regions in the mammogram. Calcifications are also bright. So the presence of pectoral muscle may leads to misleading results [7]. In order to avoid this pectoral mscles are removed in preprocessing efficiently.

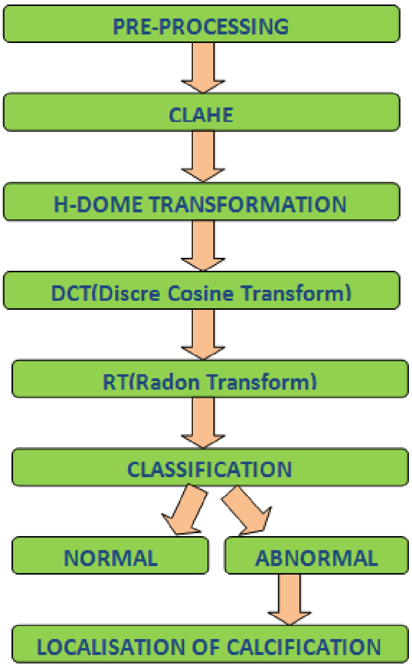

Figure 1: Block Diagram

B. Contrast Limited Adaptive Histogram Equalisation (CLAHE)

CLAHE is a technique used to improve contrast in images. Ordinary histogram equalization applies on the entire image, while adaptive histogram equalization applies on different sections of an image and in effect it improves the local contrast of the image.

C. H-dome Transformation

H-dome morphological processing is an algorithm used to extract regional maxima based on grayscale reconstruction. Grayscale reconstruction is a morphological operator based on two images instead of a single image and a SE (Structural Element). In grayscale reconstruction the original image is the mask image and marker image is created by subtracting a constant value ‘h’ from each pixel value in the mask image. Grayscale reconstruction is repeated dilations of marker image under mask image.

$$h - dome(I) = I - p_I(h) \quad (1)$$

where p_I is the grayscale reconstructed and I is the original image.

D. Feature Extraction

It includes Discrete Cosine Transform (DCT) and Radon Transform (RT).

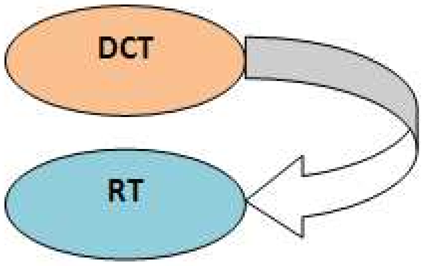

Figure 2: Feature Extraction

1) Discrete Cosine Transform: Discrete Cosine Transform transforms the mammogram from spatial domain to spectral domain. This will help in the detection of calcification. The DCT coefficients of a region containing clusterd microcalcification distributed to right and/or lower right corner of the DCT coefficient matrix.

The two-dimensional DCT of an M ×N image I(m,n) is defined as follows,

$$C_{pq} = \propto_p \propto_q \sum_{M=0}^{M-1} \sum_{N=0}^{N-1} [I(m,n) \cos \frac{\pi(2m+1)p}{2M} \cos \frac{\pi(2n+1)q}{2N}] \quad (2)$$

where, C_{pq} are the coefficients of the discrete cosine transform, and the parameters $\propto_p$ and $\propto_q$ are defined by,

$$\propto_p = \frac{1}{\sqrt{M}}, if\ p = 0; \sqrt{\frac{2}{M}}, if\ 1 \le p \le M-1 \quad (3)$$

$$\propto_q = \frac{1}{\sqrt{N}}, if\ q = 0; \sqrt{\frac{2}{N}}, if\ 1 \le q \le N-1 \quad (4)$$

2) Radon Transform: The radon transform computes projections of an image matrix along specified directions. A projection of a two-dimensional function f(x,y) is a set of line integrals. The radon function computes the line integrals from multiple sources along parallel paths, or beams, in a certain direction. The beams are spaced 1 pixel unit apart. To represent an image, the radon function takes multiple, parallel-beam projections of the image from different angles by rotating the source around the center of the image [8]. The continuous radon transform of an image I(x,y), given as,

$$R(\rho,\theta) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} I(x,y)\delta(\rho - x\cos\theta - y\sin\theta)dxdy \quad (5)$$

where δ(.) is the Dirac delta function and $\rho = x\cos\theta - y\sin\theta$ defines the perpendicular distance of all lines in the image plane which form an angle $\theta \in [0, \pi]$ with respect to the x-axis. Consequently, R(ρ, θ) represents scans of I(x,y) over the infinite set of lines defined by

$\rho - x\cos\theta - y\sin\theta = 0.$

Entropy and energy features [9] are extracted from the DCT and RT processed images. These features are calculated for each orientation of the image(0,45,90,135).ie total eight feature vectors are calculating for the classification.

E. Classification

Support Vector Machines (SVM) are employed to distinguish normal from malignant images, using the obtained feature vectors as inputs. SVM performs classification by constructing a hyperplane. The separating margin between positive and negative examples to this hyperplane is optimal. Thus separating hyperplane works as a decision surface. The important advantages of SVM classifier are,

- Execution time is very less
- Little modification in Feature Extracted Data does not affect its Results
- It is converging very fast
- SVM is performing in n-Dimensional space

F. Localization of CALCIfiCATION

Here, we are dividing the mammogram into four quadrants and perfoming the algorithm on all the quadrants. Then classifying the quadrants, wheather it is normal or abnormal using an SVM classifier. If it is abnormal, then there will be the possibility of calcification. It will help the radiologist to give more focus on that area.

IV. SIMULATION R ESULTS

The algorithm is tested using one hundred mammograms from the MIAS database. All mammograms are flipped into one direction and removed the unwanted tags and symbols in the mammogram. Original and pectoral muscle removed mammogram is shown in Figure 3.and Figure 4.

Contrast of the mammogram is enhanced using CLAHE and then Segmentation of the high frequency components of the mammograms is obtained using h-dome transformation. Obtained result is shown in Figure 5.

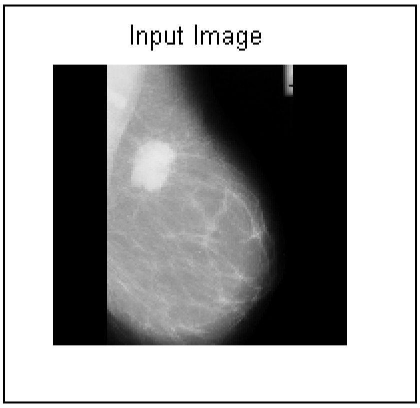

Figure 3: Original Mammogram

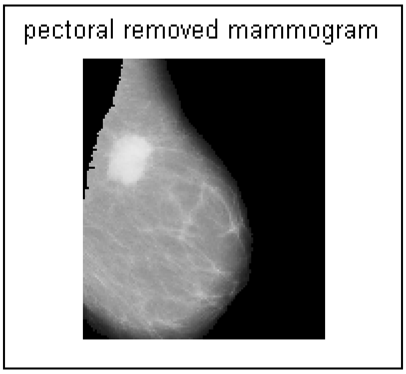

Figure 4: Pectoral Muscle Removed Mammogram

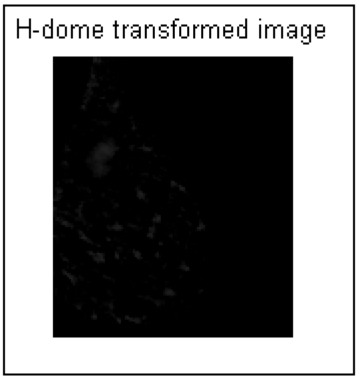

Figure 5: H-dome Transformed Image

Figure 6: Localization of Calcification

After doing the feature extraction classification is done using an SVM classifier. The performance of the classifier is analysed by,

$$Sensitivity = \frac{TP}{TP+FN} \tag{6}$$

$$Specificity = \frac{TN}{TN+FP} \tag{7}$$

Where TN, TP, FN, FP indicates True Negative, True Positive, False Negative, False Positive respectively. Classification result is shown following table. For abnormal mammograms calcification is located after dividing the mammograms into different quadrants. Quadrants of mammograms with calcification are plotted with a rectangle. Result obtained after localizing the calcification is shown in Figure 6.

Table 1: Classification Results

Test images	TP	TN	FP	FN	Accuracy	Sensitivity	Specificity
100	26	68	4	2	94	92.86	94.44

The classification accuracy of the proposed method from previous methods are shown in Figure 7. RD-DCT method shows worst classification accuracy and proposed method shows highest classification accuracy.

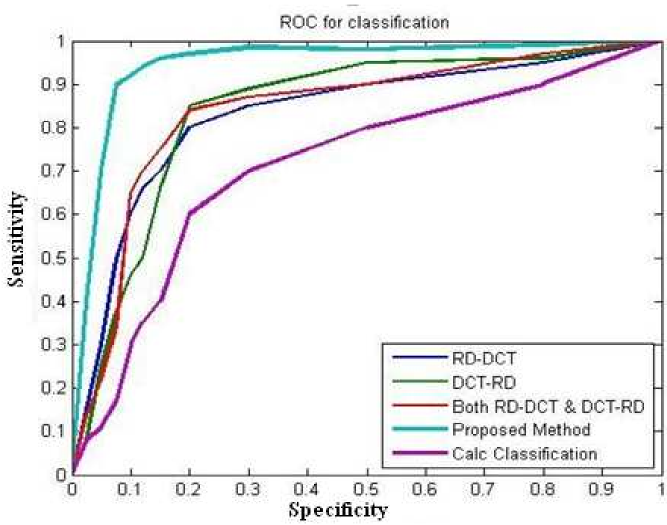

Figure 7: ROC Curve

V. CONCLUSIONS

Proposed a computer aided detection system to classify normal and abnormal mammograms. Proposed system works effectively in preprocessing and obtaining local maxima of mammogram using CLAHE and H-dome transformation. Entropy and energy feature vectors are extracted from the hybrid combination of DCT-RT process in images. Localization of calcification on any of the quadrants of the abnormal mammogram also achieved using this algorithm. Further division of mammogram decreases the localization accuracy, since most of the information may appear on the common boundary. This algorithm achieved 94% classification accuracy and 76% localization accuracy.

REFERENCES

1. Salim Lahmiri, Mounir Boukadoum, Hybrid Cosine and Radon Transform-based processing for Digital Mammogram Feature Extraction and Classification with SVM, International Conference of the IEEE EMBS, Boston, Massachusetts USA, August 30 - September 3, 2011

2. B.L. Mann, S. Nithya, Using Neural Networks with Wavelet Transforms for an Automated Mammographic Mass Classifier, IEEE Proc of the 22nd Annual EMBS international Conference, July 23-28, Chicago IL, pp. 985- 987, 2000.

3. I. Buciu, A. Gacsadi, Gabor Wavelet Based Features for Medical Image Analysis and Classification, IEEE 2nd International Symposium on Applied Sciences in Biomedical and Communication Technologies (ISABEL), November 24-27, Bratislava, Slovak Republic, pp. 14, 2009.

4. A. Farag, S. Mashali, DCT Based Features for the Detection of Microcalcifications in Digital Mammograms, IEEE International Symposium on Micro-Nano Mechatronics and Human Science, December 30, Cairo, Egypte, Vol. 1, pp: 352-355, 2003.

5. J.C. Fu, S.K. Lee, S.T.C. Wong, J.Y. Yeh, A.H. Wang, and H.K. WuImage Segmentation Feature Selection and Pattern Classification for Mammographic Microcalcifications Computerized Medical Imaging and Graphics, Vol. 29, pp. 419-429, 2005.

6. Sara Dehghani, Mashallah Abbasi Dezfooli, A Method For Improve Pre-processing Images Mammography. International Journal of Information and Education Technology, Vol. 1, No. 1, April 2011

7. D. Narain Ponraj, M. Evangelin Jenifer, P. Poongodi, J. Samuel Manoharan, A Survey on the Preprocessing Techniques of Mammogram for the Detection of Breast Cancer. Journal of Emerging Trends in Computing and Information Sciences, VOL. 2, NO. 12, December 2011

8. L. Bocchi, J. NoriShape, Analysis of Microcalcifications using Radon Transform. Medical Engineering and Physics, Vol. 29, pp. 691- 698, 2007.

9. Monika Sharma, R. B. Dubey, Sujata, S. K. Gupta, Feature Extraction of mammograms, International Journal of Advanced Computer Research,Vol-2 No-3,September-2012

10. Rafael C Gonzalez and Richard E Woods, Digital Image Processing, second edition, 2002, Prentice Hall India.