Detection of Architectural Distortion in Mammogram

Rekha Lakshmanan and Shiji T. P
Govt. Model Engineering College, Kochi, India
Email: {rekha, shiji}@mec.ac.in

Vinu Thomas
Govt. College of Engineering
Email: vt@mec.ac.in

Suma Mariam Jacob and TharaPratab
Lakeshore Hospital, Kochi, India
Email: sumajacob74@yahoo.co.in, tharapratap@hotmail.com

***Abstract*—Amethod for the detection of the most commonly missed breast cancer anomaly, Architectural distortion, is proposed here. The distorted abnormal structures associated with Architectural distortion in suspicious regions are extracted using geometrical properties of edge features based on an energy model. Contours obtained from a modified Single Univalue Segment Assimilating Nucleus filtered mammogram, are employed for this purpose. A Pectoral muscle delineation technique is incorporated in the proposed method to reduce false positive rate.A ranking value of these potential regions based on linear and converging properties is computed to identify the probable origins of architectural distortion. Experimental analysis is performed on 100 images obtained from Lakeshore Hospital, India. The results are verified by expert radiologists. The proposed algorithm is successful in 94 mammograms and the results are found to be promising.**

***Index Terms*—mammograms, modified SUSAN filter, Energy model, shortest centroid distance, ranking metric, Architectural distortion**

I. Introduction

About 25-31% of cancer occurrences in India are that of breast cancer [1], where it becomes one of the leading causes of fatality among women. Even though the incidence of breast cancer in India is lesser compared to developed countries like U.S and China, mortality is very high. According to the statistics in 2013 of World Health Organization (WHO), 70,218 women inIndia died due to breast cancer [2]. As per the statistics by WHO, one among two Indian women who are newly diagnosed with breast cancer has lost her life due to the cause.

Architectural distortionis a major symptom of breast cancer. It is the considered as the most commonly missed abnormality during screening [3]. Around 12-45% of the cases of breast cancers missed in screening are found to have had Architectural distortion in the mammograms [3]. 48-60% of Architectural distortion cases biopsied are found to be cancerous and 80% of them are invasive in nature [4].

Architectural distortion is detected by identifying the distorted architecture of breast structure [3]. Distortion of architecture includes either radiating patterns with no mass visible or distortion at the edge of parenchyma [5]. The presence of normal breast parenchyma, dense tissues, and the subtle nature of abnormal structures obstruct the visibility of malignant structures. Usually architectural distortion is associated with other abnormalities such as calcifications or mass [6]. Computer aided methods (CAD) are very effective supporting tools for radiologists to analyze mammograms [7]. CAD detection of Architectural Distortion is a challenging research area due to the difficulty in identifying the presence of abnormal structure [8].

Most of the literature on detection of architectural distortion concentrates on the breast tissue pattern of mammograms [9]-[13]. Concentration index and morphological image processing were applied by Matsubara *et al.* [9] to obtain a sensitivity of 84%. Sampat *et al.* [10] applied Radon transform and a linear filter to yield a sensitivity of 80%. Etonsy *et al.* [11] detected architectural distortion by identifying points along concentric layers achieving a sensitivity of 93.1%. Guo *et al.* [12] achieved a classification accuracy of 72.5 % for architectural distortion using Hausdorff distance and Support Vector Machine. Rangayyan *et al.* [13] proposed a method for measuring the divergence of oriented patterns from normal patterns attaining 80% sensitivity. S. Banik succeeded in detecting the probable architectural distortion sites using a bank of Gabor filters, linear phase portrait modeling and different types of entropies [14].

The method proposed here narrows down the Region of Interests (ROIs) in the mammogram image using a modified version of SUSAN filtering [15]. Geometrical properties of extracted edge features from these ROIs are

Manuscript received July 10, 2014; revised November 21, 2014.

doi: 10.12720/joig.2.2.123-127

employed for detecting origin of architectural distortion. The centroids of such identified regions with more numberof linear converging tissue structures indicate the origin of promising location for Architectural distortion. The proposed method also reduces false positivesby removing the pectoral muscle (PM) region.

II. PROPOSED METHOD

The two major properties of patterns in the abnormal regions utilized by the proposed method for Architectural distortion are listed below.

- Abnormal patterns are linear in nature [16].
- Distorted patterns concentrate towards the distorted area whereas normal patterns concentrate towards the nipple [6].

A preprocessing operation is performed to extract the region of interest by removing unwanted artifacts such as noise, labels and wedges as well as PM region. The potential sites of architectural distortion are identified using contours of the resultant image obtained after filtering with a modified Single Univalue Segment Assimilating Nucleus (SUSAN) filter. Edge features of these regions are further geometrically analyzed to remove normal tissue patterns.

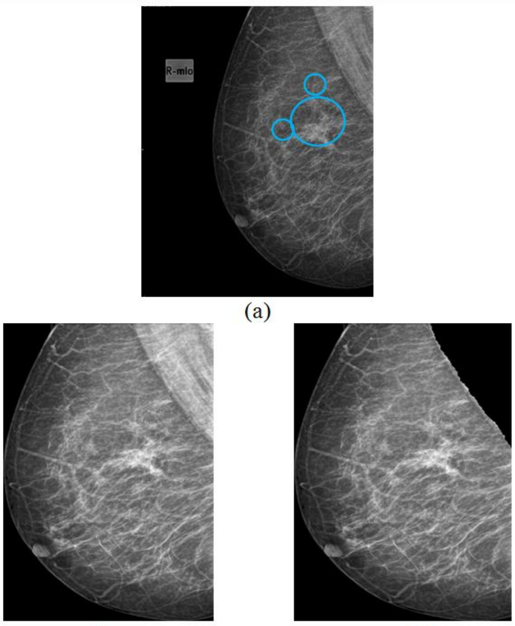


Figure 1. Mammographic region of interest extraction. (a) Original image. Blue circle shows the region of Architectural distortion, Image after removing (b) unwanted artifacts such as labels, noise (c) pectoral muscle region.

A metric is used to identify the prominent site of architectural distortion. The steps for the proposed technique are explained below.

A. Extraction of the Mammographic Region

The mammographic region which the radiologist analyses for breast cancer is extracted by removing noise, wedges, labels, pectoral muscle etc. A large area component after thresholding and Weiner filtering [17] can be utilized for PM removal. The threshold employed here, TH depends on the minimum and maximum intensity value of mammographic image is defined as

$$TH = \left(I_{\min} + I_{\max}\right) \times 0.05 \tag{1}$$

where $I_{\min}$ and $I_{\max}$ are the minimum and maximum intensity value of image, I respectively. The PM region is obtained using geometrical properties of edge structures on a multi scale decomposed image [18].

Fig. 1 shows the result of mammographic region extraction on a mammographic image collected from Lakeshore Hospital.

B. Isotropic Filtering and Contour Extraction

Architectural distortion, the most commonly missed abnormality usually appears as radiating patterns distributed in different directions originating from a central region with no definite central mass [14]. The radiating patterns differ from the normal patterns in the region of convergence. The normal patterns are directed towards the nipple where as the abnormal patterns concentrate towards the origin of distortion [14]. The origin of distortion appears as a central homogeneous region [11]. Structural regions of mammographic image are categorized into various homogeneous regions based on the principle of intensity similarity. SUSAN filtering [16], a local segmentation technique, is useful in finding such homogeneous regions that are potential candidates of Architectural Distortion features. Here, a local area of similar intensity for each pixel is identified by moving a circular mask over the whole image. The isotropic nature of the circular mask provides response in all directions. The pixel considered for processing is called the nucleus and the local circular area of image inside circular mask is called Univalue Segment Assimilating Nucleus (USAN). The response of the filter for each block is obtained by comparing an exponential function of intensity dissimilarity with a threshold value. The response of the filter for a local circular region is given as

$$c(\vec{r},\vec{r_0}) = e^{-\left(\frac{(I(\vec{r})-I(\vec{r_0}))}{t}\right)^6} \tag{2}$$

where I is the image and $\vec{r}$ and $\vec{r_0}$ are the nucleus and a pixel in the USAN area respectively. t is a user - defined brightness difference threshold taken as $2(I_{max} + I_{min})$ in this work, where I_{max} and I_{min} are the maximum and minimum values of I. The accumulated sum of $c(\vec{r},\vec{r_0})$ over $\vec{r}$ as $n(\vec{r_0})$ is compared with a global threshold g $=3n_{max}/4$, where n_{max} is the maximum value of n, to decide whether the pixel should be included in the local region or not.

0	0	1	1	1	0	0
0	1	1	1	1	1	0
1	1	1	1	1	1	1
1	1	1	1	1	1	1
1	1	1	1	1	1	1
0	1	1	1	1	1	0
0	0	1	1	1	0	0

(a)

0	1	1	0	1	1	0
1	0	0	0	0	0	1
1	0	1	1	1	0	1
0	0	1	1	1	0	0
1	0	1	1	1	0	1
1	0	0	0	0	0	1
0	1	1	0	1	1	0

(b)

Figure 2. SUSAN and modified SUSAN filter

In the proposed method, SUSAN filter is modified to identify the central homogeneous regions along with surrounding radiating patterns. Fig. 2 shows the SUSAN filter and the modified SUSAN filter. The modified SUSAN filter reduces the search area in the mammographic image compared to SUSAN filter. It is also able to search for radiating structures emanating from a central homogeneous region, without missing any of such central regions.

Contours of the reduced regions are identified. Fig. 3(c) and 3(d) indicate the contour plots obtained from the SUSAN filter output as shown in Fig. 3(a) and the modified SUSAN filter output in Fig. 3(b). On comparison, it is seen that the identified contours are far less in number for that of the modified SUSAN filter. This is true for all the images on which the algorithm has been tried on. The regions identified using the modified SUSAN filter does not miss out on the Architectural Distortion features, as verified by the radiologist.

Centroids [19] of these contours represent the origin of the potential site of architectural distortion. Centroids and areas of closed polygons corresponding to each contour are calculated using the contour coordinates as per equations (3) – (5).

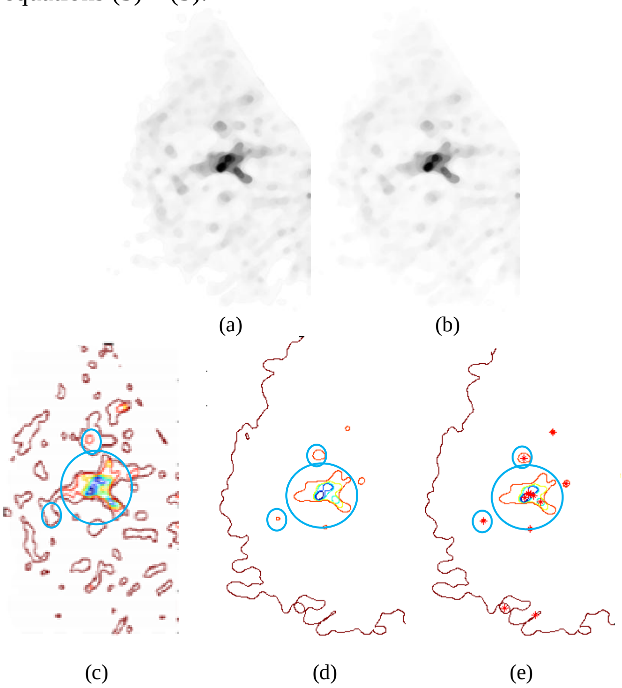


Figure 3. Mammographic image after (a)SUSAN filtering (b) modified SUSAN filtering, contour extraction using (c)SUSAN filtering and (d) modified SUSAN filtering technique.Blue circle shows the boundary of ground truth information

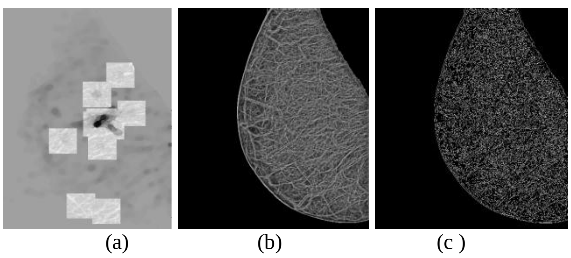


Figure 4. (a)Mammographic regions around detected centroids, (b) Edge features, (c) thinned edge features

The central originating point of architectural distortionis found to be close to one of these centroids.

$$C_x = \frac{1}{6A}\sum_{i=0}^{N-1}(x_i + x_{i+1})(x_i y_{i+1} - x_{i+1} y_i) \tag{3}$$

$$C_y = \frac{1}{6A}\sum_{i=0}^{N-1}(y_i + y_{i+1})(x_i y_{i+1} - x_{i+1} y_i) \tag{4}$$

$$A = \frac{1}{2}\sum_{i=0}^{N-1}(x_i y_{i+1} - x_{i+1} y_i) \tag{5}$$

here x_i and $y_i$are the coordinates of the contour with i ranging from 0 to $N\text{-}1$, N being the number of vertices in the contour. C_x and $C_y$are the coordinates of contour centroid and A is the contour area. Fig. 3(e) shows the centroids as blue spots on contours of modified SUSAN filtered mammographic image.

The further steps of the algorithm work on the centroids identified at this stage.

C. Region of Interest Extraction

A mammographic region of size 200×200 around each centroid is chosen for further processing. Fig. 4(a) shows the selected mammographic regions around centroids overlapped on modified SUSAN filtered image.

D. Edge Feature Extraction

Mammographic image consisting of various structures can be identified using an energy based edge feature extraction technique which in turn is based on an energy model. According to this model, features can be extracted from points where the frequency components are maximally in phase [20]. The one dimensional phase congruency is computed as

$$PC(x) = \frac{|E(x)|}{\sum_n A_n(x)} = \frac{\sum_n A_n(x)\cos(\varphi_n(x) - \bar{\varphi}(x))}{\sum_n A_n(x)} \tag{6}$$

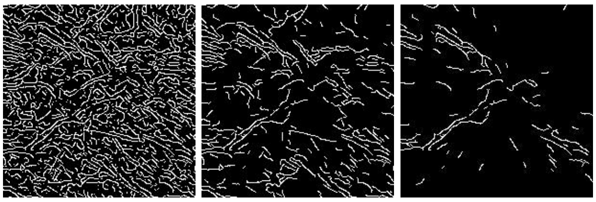
where $A_n(x)$ is the length, $\phi_n(x)$ is the phase angle of each of n individual vectors of Fourier components at location x, $E(x)$ is the length(energy) and $\bar{\phi}(x)$ is the phase angle of the summed vectors. A group of log-Gabor Wavelets at N different scales and M orientations are used to extend the equation (6) in two dimensions to compute phase congruency. The advantage of Log Gabor transform for radial filtering is that it is Gaussian on a logarithmic scale and hence has better high frequency characteristics than the conventional Gabor transform [20]. Such edge features obtained from the reduced suspicious regions are thinned, based on the principle of gradient magnitude maximization [21]. Fig. 4(b) represents edge features of mammographic images using the principle of phase congruency. Strong edge features obtained using thinning method is shown in Fig. 4(c).

E. Implementation of Geometrical Properties

In a mammogram, architectural distortion usually appears as radiating patterns originating from a central region whereas the normal tissue structures directed towards the nipple point. Fig. 5 shows the normal and abnormal patterns of tissue structure obtained from a mammogram after filtering operation. The normal tissue patterns of ducts, blood vessels, ligaments etc in the affected region may affect the identification of abnormal tissues associated with architectural distortion. The linear and converging properties of abnormal patterns are employed for removing the normal patterns in the selected regions after contour extraction.

(a) (b)

Figure 5. Tissue structure pattern (a) normal region (b) abnormal region.



(a) (b) (c)

Figure 6. (a) Tissue structures after thinning (b) structures satisfying linearity property(c) structures satisfying converging property in one of selected abnormal region.

(a) (b) (c)

Figure 7. (a) Tissue structures after thinning (b) structures satisfying linearity property (c) structures satisfying converging property in one of selected normal region.

The linear radiating tissue structures in the processed mammographic image are identified by applying the eccentricity property [18]. In order to find the tissue structures converging towards the origin of distorted region, only linear tissue structures passing near to the centroid of selected region are considered. Each linear structure is extended to the boundary of selected region for finding its proximity towards the centroid. A linear structure satisfying a threshold criterion is retained and the others are rejected. The results of thinned breast tissue structuresafter applying the geometrical properties for a normal and abnormal breast region are shown in Fig. 6 and Fig. 7 respectively. The total number of linear converging structures as well as a normalized value is the major factors for selecting a region as abnormal. The normalized value in a selected region is obtained as the ratio between number of linear converging lines and number of linear lines in that region. On analysis, it is seen that a region with a minimum 35 number of linear converging lines and the ratio as 25 or above can be considered as malignant region The proposed algorithm was simulated on 100 mammographic images from Lakeshore Hospital and the results obtained were verified with clinical findings of the radiologists.

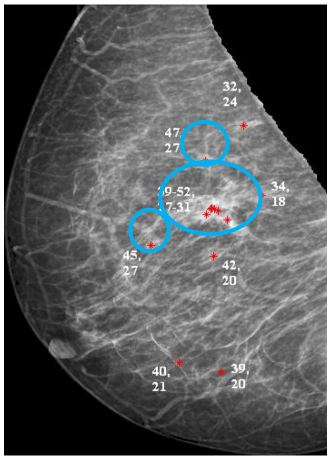


Figure 8. Ranking values based on total number of linear lines satisfying converging property along with its ratio with linear line. Blue circle shows ground truth of information provided by radiologist.

Fig. 8 shows the result of ranking values in one of the mammographic image collected from Lakeshore Hospital. The ground truth is shown using blue circular plot and the centroids obtained by the proposed method are shown as red spots.

III. Conclusion

The proposed method is a promising technique for detecting the most commonly missed abnormality, Architectural distortion. The results obtained for this method, utilizing the linearity and converging property of abnormal patterns towards the distorted area is encouraging. The proposed method successfully identified 94 images out into 100 as normal and abnormal classes and was verified with expert radiologists in Lakeshore Hospital, Kochi, India. A classification method with more features can be utilized as a future work for analyzing the probable regions of Architectural Distortion to increase the accuracy of the proposed method.

Acknowledgment

The authors wish to thank the Lakeshore Hospital, Kochi, India authorities for their support. This work was supported by State Council for Science, Technology and Environment (KSCSTE) and Technical Education Quality Improvement Programme (TEQIP-II) of the Ministry of Human Resources Development, Govt. of India.

References

[1] Three Year Report of Population Based Cancer Registries 2009-2011, National Cancer Registry Programme. Banglore, India: NCDIR, Indian Council of Medical Resaerch (ICMR), 2013.

[2] International Agency for Research on Cancer Fact sheet. [Online]. Available: http://www.globocan.iarc.fr/factsheet.asp

[3] A. M. Knutzen and J. J. Gisvold, "Likelihood of malignant disease for various categories of mammographically detected, nonpalpable breast lesions," in *Proc. Mayo Clinic*, no. 68, 1993, pp. 454-460.

[4] J. A. Johnston and C. Z. Clee, "Analysis of 308 localisation breast biopsies in a New Zealand hospital," *Australas Radio l.*, vol. 2, no. 35, pp. 148-51, May 1991.

[5] J. Tang, R. M. Rangayyan, J. Xu, I. E. Naqa, and Y. Yang, "Computeraided detection and diagnosis of breast cancer with mammography: Recent advances," *IEEE Trans. Inf. Technol. Biomed*, vol. 13, no. 2, pp. 236-251, 2009.

[6] M. P. Sampat, G. J. Whitman, M. K. Markey, and A. C. Bovik, "Evidence-based detection of spiculated masses and architectural distortions," in *Proc. SPIE Medical Imaging: Image Processing*, San Diego, vol. 5747, 2005, pp. 26-37.

[7] T. Matsubara, T. Ichikawa, T. Hara, H. Fujita, S. Kasai, T. Endo, and T. Iwase, "Novel method for detecting mammographic architectural distortion based on concentration of mammary gland," in *Proc. 18th International Congress and Exhibition on Computer Assisted Radiology and Surgery*, International Congress Series, Elsevier B.V., vol. 1268, 2004, pp. 867-871.

[8] J. A. Baker, E. L. Rosen, J. Y. Lo, E. I. Gimenez, R. Walsh, and M. S. Soo, "Computer-Aided Detection (CAD) in screening mammography: Sensitivity of commercial CAD systems for detecting architectural distortion," *Am J Roentgenol*, vol. 181, pp. 1083-1088, 2003.

[9] T. Matsubara, T. Ichikawa, T. Hara, H. Fujita, S. Kasai, T. Endo, and T. Iwase, "Automated detection methods for architectural distortions around skinline and within mammary gland on mammograms," *CARS*, pp. 950-955, 2003.

[10] M. P. Sampat, G. J. Whitman, M. K. Markey, and A. C. Bovik, "Evidence based detection of spiculated masses and architectural distortion," in *Proc. SPIE Medical Imaging: Image Processing*, San Diego, CA, vol. 5747, April 2005, pp. 26-37.

[11] N. Eltonsy, G. Tourassi, and A. Elmaghraby, "Investigating performance of a morphology based CAD scheme in detecting architectural distortion in screening mammograms," in *Proc. 20th International Congress and Exhibition on Computer Assisted Radiology and Surgery*, 2006.

[12] Q. Guo, J. Shao, and V. Ruiz, "Investigation of support vector machine for the detection of architectural distortion in mammographic images," *Journal of Physics: Conference Series*, vol. 15, pp. 88-94, 2005.

[13] R. M. Rangayyan, S. Banik, J. Chakraborty, S. Mukhopadhyay, and J. E. L. Desautels, "Measures of divergence of oriented patterns for the detection of architectural distortion in prior mammograms," *Int J CARS*, vol. 8, pp. 527-545, 2013.

[14] S. Banik, R. M. Rangayyan, and J. E. Leo Desautels, "Measures of angular spread and entropy for the detection of architectural distortion in prior mammograms," *International Journal of Computer Assisted Radiology and Surgery*, vol. 8, pp. 121-134, 2013.

[15] Smith and J. Brady, "SUSAN-a new approach to low level image processing," *IJCV*, 1997.

[16] B. Hashimoto, *Practical Digital Mammography*, Thieme, 2011.

[17] P. Mayo, F. Rodenas, and G. Verdu, "Comparing methods to denoise mammographic images," in *Proc. 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, vol. 1, Sept. 2004, pp. 247-250.

[18] R. Lakshmanan, T. P. Shiji, V. Thomas, S. M. Jacob, and T. Pratab, "Pectoral muscle boundary detection–A preprocessing method for early breast cancer detection," accepted in IFMIP, World Automation Congress, August 3-7, 2014.

[19] P. Bourke, "Calculating the area and centoid of polygon," July 1998.

[20] P. Kovesi, "Image features from phase congruency," *Videre: Journal of Computer Vision Research*, vol. 1, 1999.

[21] J. Canny, "A computational approach to edge detection," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 8, pp. 679-698, 1986.

Rekha Lakshmanan is pursuing her PhD at Govt. Model Engineering College, Kochi, India. She received her M.Tech in "Digit Image Computing" from Kerala University in 2008 and B.Tech in Computer Science and Engineering from CUSAT in 2001. Her area of interest is image processing. She has 16 publications to her credit in international conferences and journals.

Shiji T. P is working as Associate Professor at the Govt. Model Engineering College, Kochi, India. She is doing her research in Medical Image Processing. She received her B.Tech degree in Electronics & Instrumentation from College of Engineering in 1994, Thiruvananthapuram and M.Tech in Optoelectronics & Laser Technology from International School of Photonics, CUSAT in 2004. She has more than 19 years of teaching experience. Her Research interests include Medical Signal and Image Processing.

Vinu Thomas received his B.Tech in Electronics & Communication from Mar Athanasius College of Engineering Kothamangalam in 1993 and M.Tech and PhD Degrees in Electronics from Cochin University of Science & Technology (CUSAT) in 2001 and 2009 respectively. He was the University topper and Gold Medalist for M.Tech in 2001. He has more than 50 papers international and national journals conferences. His research interests include Multi Resolution Signal & Image Processing, Artificial Naaaeural Networks, Array Processing and Computational Electrodynamics. He is affiliated to College of Engineering, Cherthala, India.

Suma MariamJacob received her MBBS and DMRD from Christian Medical College, Vellore in 1993 and 2001 respectively. She received her DNB in 2008 and is currently working as Consultant Radiologist, Lakeshore Hospital, Kerala, India. She was awarded as the Best radiology student by CMC Vellore for the year 2001. She secured Best paper prize for RADIOLOGY among post graduate students conducted by Kerala IRIA chapter in 2007.

Thara Pratab is a Senior Radiologist with 14 years of experience. She completed her MBBS, MD, DMRD and DNB from Trivandrum Medical College in the year 1994, 1999, 2000 and 2001 respectively. She did her MD with specialization in radiology. She was working at the Lissie Hospital, Kochi, India during 2000-2003. She is currently affiliated to the Lakeshore Hospital, Kochi, India.