SIViP
DOI 10.1007/s11760-016-1018-y

ORIGINAL PAPER

Asymmetry analysis of breast thermograms using automated segmentation and texture features

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Received: 9 May 2016 / Revised: 7 September 2016 / Accepted: 1 November 2016

Abstract In this article, we present a new approach for breast thermogram image analysis by developing a fully automatic segmentation of right and left breast for asymmetry analysis, using shape features of the breast and Polynomial curve fitting. Segmentation results are validated with their respective Ground Truths. Histogram and grey level co-occurrence matrix-based texture features are extracted from the segmented images. Statistical test shows that features are highly significant in detection of breast cancer. We have obtained an accuracy of 90%, sensitivity of 87.5% and specificity of 92.5% for a set of eighty images with forty normal and forty abnormal using SVM RBF classifier.

Keywords Breast cancer · Breast thermography · Asymmetry analysis · Texture features · Bifurcation line · Statistical test

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1 Introduction

Breast cancer is the most commonly detected disease in females everywhere. Due to the change in lifestyle factors, rapid growth of industries, urbanization resulted in a gradual increase in the incidence of breast cancer [23]. Early detection of breast cancer increases the rate of survival of women by providing proper treatment [15,31]. Medical imaging techniques like mammography, ultrasound and magnetic resonance imaging (MRI) techniques are used for detection of early signs of breast cancer. Mammography is commonly used technique for detecting the breast abnormalities. But mammograms do not work well in women with dense breasts, since dense breasts can hide a tumour [9,15]. Hence it may increase the false-positive or false-negative rate in such patients. Image formation in mammography requires X-ray radiation, which may increase the risk of future cancer growth [30]. Also mammography procedure is uncomfortable to women due to the compression of the breast [30]. Breast thermography is considered to be the developing medical imaging tool, which monitors the physiological changes occurring in the breast. It can detect breast cancer in its early stage before structural change occurs in the breast [10]. Breast thermography is a very useful imaging technique for risk assessment and early detection. It can be used for women of all ages, all breast densities, breast implants and monitoring of the breast after surgery [9,10]. Further, thermography is a non-invasive, non-ionizing, painless, safe and simple medical imaging technique [30]. Breast thermography is based on infrared radiation of the breast. It measures the vascular heat radiated from the surface of the breast [26]. The growing tumour has a higher metabolic rate and associated increase in local vascularization [15]. The abnormal thermogram image can be differentiated from the normal thermogram by the presence of asymmetric heat pat-

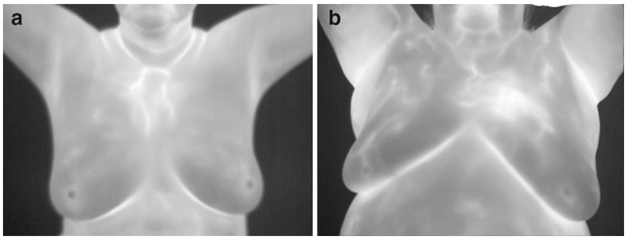

Fig. 1 Examples for breast thermograms. **a** Normal breast **b** abnormal breast

terns in the right and left breast [17]. Figure 1 shows an example for normal and abnormal breast. Temperature distributions in the right and left breast are symmetric in Fig. 1a and asymmetric in Fig. 1b, as the patient is suffering by infiltrating ductal carcinoma in union of upper quadrants in left breast. Physicians look for such abnormalities and analyse subjectively, but it is not possible to detect all kinds of asymmetries present in the breast thermogram image for a naked eye. Computer-aided detection (CAD) systems could help physicians in providing additional information on abnormalities present in the medical images [2,19]. In the proposed method, we have obtained an accuracy of 90%, sensitivity of 87.5% and specificity of 92.5% in classifying abnormal and normal breast thermograms.

2 Related work

Research groups are working on the development of CAD for breast thermography. Due to the ambiguous nature of breast thermograms, some research groups have used manual segmentation or semi-automated segmentation [3,13,17,27]. Araujo et al. [3] evaluated the feasibility of using interval data in symbolic data analysis (SDA) framework to model breast abnormalities as malignant, benign and cyst. Their segmentation method used ellipsoidal elements for selecting the area of each breast. Ellipses were adjusted for the patient's breast, by manually selecting the diameter of ellipse. Minimum and maximum temperature values were extracted from the morphological and thermal matrices. Schaefer et al. [27] extracted various statistical features from temperature, histogram and cross co-occurrence matrix. They also extracted spectral features from the Fourier spectrum of thermal image [13]. Breast thermogram images were segmented manually by experts as left and right breast. The extracted features were fed to a fuzzy classification system and they obtained 80% accuracy in classification.

To detect the breast cancer in faster rate and more accurate, an appropriate automated segmentation is very much essential. The papers [7,20,21,25,29] describe automated segmentation of breast thermograms for asymmetry analysis. Moghbel et al. [20] used random walker-based segmentation method, where circular Hough transforms were applied to the image to find most likely candidates for the areola area and analysed them based on intensity variations. But their segmentation fails for poor intensity distributed breast thermogram images. Motta et al. [21] developed an automated segmentation method, which used thresholding based on highest temperature of the breast for the detection of lower border. Upper limit of region of interest (ROI) is obtained by detecting axilla. The centre point of the segmented image is used for separating right and left breast. But in an asymmetric breasts, the centre point of the breast may not detect right and left breast ROI separation point. Borchartt et al. [7] used a segmentation procedure proposed by Motta et al. [21] and Hough transform. They used range of temperature in ROI, the mean temperature, standard deviation and quantization of the higher tone in an eight level posterization. These features were extracted from the entire breast image and breast quadrants. Support vector machine classifier gave an accuracy of classification around 86%. Qi et al. [25] used Canny edge detection followed by Hough transform for the detection of lower boundaries of the breast. Here authors assumed that lower breast boundary is parabolic in shape. In an abnormal and asymmetric breasts, generalization of lower boundary as parabola may result in error in the detection of ROI of breast. The Hough transform method is also highly computationally expensive. De Souza Marques [29] extended the method proposed by Motta et al. [21] by joining the detected edges of the image boundary by quadratic B-Splines.

In this article, a novel segmentation method for asymmetry analysis of breast thermograms is proposed, by making use of shape features of the breast and Polynomial curve fitting. Normally, frontal view of breast thermogram images has concave and convex shape in the upper and lower part of breast [16,18]. These shape features are utilized in the proposed method for detecting lateral and upper boundary of the breast. The breast images have inframammary folds at the bottom of the breast, where chest and breast meet. These inframammary folds of the breasts are detected by horizontal projection profile (HPP) method to locate the lower boundary of the breast. To segment right and left breast, we apply polynomial curve fitting on inframammary edges. These polynomial curves are extended upwards to find the bifurcation point, where the right and left breast meet. This curve fitting method appropriately model the inframammary curves, so that ROI of right and left breast is accurately determined for asymmetry analysis. The proposed method of segmentation accurately detects ROI for almost all breast images present in the database used. Figure 2 shows the block diagram representation of the proposed segmentation method. Segmentation results of the proposed method are validated using ground truth (GT) masks, obtained by manually segmenting the breast thermogram image and verified by the physician. Histogram- and GLCM-based texture features are extracted from segmented

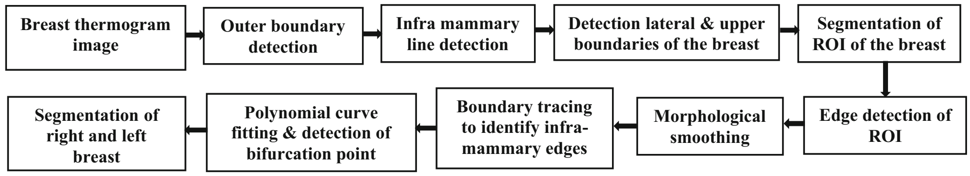

Fig. 2 Block diagram representation of the proposed segmentation method

right and left breast. Absolute difference of these features between right and left breast is computed for asymmetry analysis. Significant features are selected for classification by performing statistical *t* test. SVM classifier with various kernel functions are used for classifying the breast thermograms into normal or malignant cases. All the processes mentioned above are explained in detail in the next sections.

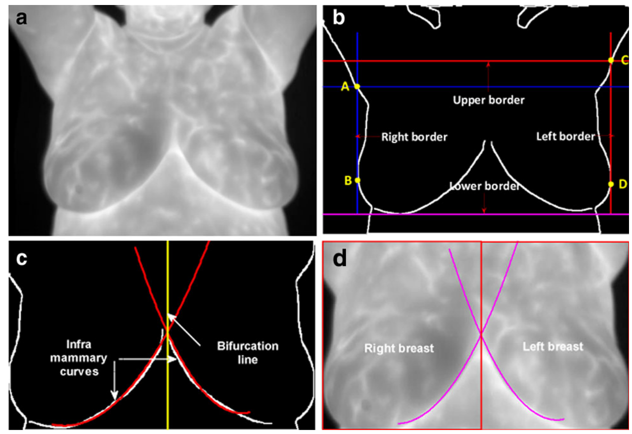

Fig. 3 Segmentation process. **a** Original thermogram image **b** Detection of outer borders. **c** Polynomial curve fitting. **d** Segmentation of right and left breast

3 Materials and methods

3.1 Image database

Data used in this work are collected from the public database at visual lab, Fluminense Federal University, Brazil [24]. Eighty frontal view static breast thermogram temperature matrices with forty normal and forty abnormal cases are considered for study. These original temperature matrices are mapped to grey intensity values from 0 to 255 to consider minute variations in the breast for early detection of cancer. It is reported that [4,28] breast thermograms were captured using FLIR infrared camera with a temperature sensitivity of 0.04 °C and pixel resolution of 640 × 480 pixels. The population has a set of patients with confirmed tumour by clinical exam, ultrasound, mammography and biopsy exams. In the proposed work, we have used various abnormal image cases like infiltrating ductal carcinoma, ductal carcinoma in situ, papillary carcinoma, lobular carcinoma in situ and fibroadenoma.

3.2 Segmentation of ROI of breast

The breast thermogram image is smoothed using a Gaussian filter with a standard deviation; $\sigma = 1.4$ to reduce noise. The value of σ is determined based on experiments to preserve inframammary edges for all images used in this work. This is followed by Canny edge detection. The detected outer boundary is dilated by morphological dilation operation in order to make it suitable for further processing to find breast boundaries. This process uses 3 × 3 structuring element.
Lower border of breast image is detected by identifying inframammary line of the breast. HPP approach is used for the detection of the inframammary line. HPP is a histogram of one dimensional array with a number of entries equal to the number of white pixels in each row. HPP is applied from the bottom of the image to the top. In the inframammary line, HPP value is high due to fold of the breast. The row number corresponding to the first high HPP is taken as the lower limit for the segmentation of the breast thermogram image.

The frontal view of breast image has concave shape in the upper part and convex shape in lower part of the breast [16,18]. By making use of these features of the breast, right, left and upper borders of the breast are detected. Due to the convexity and concavity of the breast, few vertical lines with a width of one pixel can be drawn through arm and breast area on either side of the breast. The first vertical line coinciding breast and arm on either side of the breast is detected. Right and left limits are identified with respect to coinciding pixel values of the lines on the breast, and they are shown by points *B* and *D* in the Fig. 3b. Upper limits for right and left breast are also recorded based on coinciding pixel values of those lines in the arm (points *A* and *C* respectively in Fig. 3b.) Final upper border is selected based on the highest value of upper limits in order to avoid loss of information present in the breast. ROI of the breast is obtained based on the detected lower, upper, right and left borders.

3.3 Segmentation of right and left breast for asymmetry analysis

Asymmetry analysis is the common method used for detecting breast cancer using breast thermogram images [6,25]. To perform asymmetry analysis, it is necessary to find the intersection point of two inframammary curves to separate right and left breast. Due to the unclear nature of breast thermograms, it is difficult to find the complete edges of inframammary curves in most of the thermograms. So, Gaussian smoothing is performed, followed by adaptive thresholding by Canny to extract the inframammary curves of the segmented ROI. In order to join broken edges, morphological closing operation is done on detected inframammary curves. Inframammary curves are the two longer curves found in breast thermograms at the lower half projecting towards centre of the image. Boundary tracing is performed to find the pixel locations of these curves. Detected curves are sorted in ascending order based on length. First two longer curves are selected, and polynomial curve fitting is applied on these curves and extended upwards to find the bifurcation point. Figure 3c. describes the detection of bifurcation point of the breast thermogram image. Figure 3d. shows the segmented thermogram image with Polynomial curves. Pseudocode for the proposed work is given below.

Algorithm: Detection of Bifurcation point
Input: Segmented ROI Image B_{seg}
Output: Bifurcation point bi, right breast image B_r and left breast image B_l
1. Find Canny edge detected image of B_{seg}
$B_{segedge} = \text{Canny}(B_{seg})$
2. Define A: Flat disc-shaped structuring element with radius 4
3. Apply Morphological closing on B_{seg} with structuring element A
D = morph close($B_{segedge}$, A)
4. Trace the boundary of the morphological closed image and sort it in ascending order
$b = boundarytrace(D), sort(b)$
First two longer boundaries near the centre of breast are denoted as $b1$ and $b2$, which are inframammary curves
5. Apply Polynomial curve fitting on $b1$ and $b2$ and find the intersection point bi
6. Segment the image B_{seg} into right breast B_r and left breast B_l by using bi.

3.4 Validation of segmentation results

Segmentation results of the proposed method are compared quantitatively with their respective GT images. Segmentation error can occur due to inaccurate detection of outer borders or bifurcation point. Quantitative measures used for validating segmentation results are mean square error (MSE) or peak signal to noise ratio (PSNR), Eucledian distance (ED) and Jaccard coefficient. MSE and PSNR [8] are defined as,

$$\text{MSE} = \frac{1}{NM} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} e(m,n)^2 \quad (1)$$

where $e(m, n)$ is the error between the segmented and GT image.

$$\text{PSNR} = 10 \log \frac{S^2}{\text{MSE}} \quad (2)$$

where S is maximum possible pixel value of an image.
Jaccard Coefficient measures the overlap between two images [14]. JC of two images A and B is given by,

$$\text{JC} = \frac{A \cap B}{A \cup B} \quad (3)$$

To measure the segmentation error due to outer borders, we detect the edges of segmented breast and its respective GT using Canny. Then these two images are subtracted. MSE and PSNR are computed for the subtracted image. JC is computed by overlapping GT image and segmented binary image. To find the accuracy of detection of bifurcation line by the segmentation algorithm, we measure the Euclidean distance between the bifurcation line detected by the segmentation algorithm and its GT image.

3.5 Feature extraction and classification

Temperature variations in thermogram images are represented by its texture. High-frequency variations are enhanced prior to feature extraction by amplifying high-frequency component present in the ROI of right and left breast using 3×3 spatial nonlinear sharpening filter. First- and second-order statistical features are extracted by computing histogram and GLCM of the ROI. Mean, variance, skewness, kurtosis and entropy are computed from histogram of the image. Neighbourhood relations of pixels are determined by computing GLCM of the image [1]. It is measure of how often various combinations of grey levels co-occur in an image. We have computed GLCM matrices in four directions, horizontal, left diagonal, vertical and right diagonal at a distance of 1 pixel. Mean, variance, entropy, contrast, correlation, energy and homogeneity features are computed from the four GLCMs. Since the cancer development in the breast is chaotic, average value of features obtained from GLCM at four directions is calculated. Absolute difference of each feature from ROI of right and left breast is computed to measure the asymmetry between right and left breast and then normalized.

SVM classifier is used for training and testing the significant features, which are selected based on independent t test. SVM is the most popular two class classification technique developed based on statistical learning theory. It uses hyperplane to separate two different classes in the given feature space. Kernel transformations are used for nonlinearly separable features [12]. To obtain higher classification accuracy, we have tested SVM with various kernel functions like linear, radial basis function(RBF), polynomial, quadratic and multilayer perceptron (MLP). Accuracy of classification is computed by leave one out cross-validation. Each time 79 samples are used for training, and one left out sample is used for testing. All the 80 samples are tested by the classifier by repeating the training and testing 80 times.

4 Results and discussions

Accurate segmentation of breast thermogram image is the first essential phase for the development of CAD of breast cancer. An appropriate automated segmentation of breast thermograms mainly depends on how accurately the ROI of the breast is detected. Since the article discusses asymmetry analysis, detection of bifurcation line is crucial for right and left breast segmentation. Any variation in the detection of bifurcation line results in inaccurate asymmetry analysis. As discussed in Sect. 3.4, the mean ± SD of validation measures such as MSE, PSNR, JC and ED for normal and abnormal cases is shown in Table 1. High values of MSE,ED and low values of PSNR, JC are obtained for abnormal breasts compared to normal breasts. This could be because of shape asymmetry and presence of more false edges in abnormal thermograms. It is also observed that the error(ED) between detected bifurcation line by the segmentation algorithm and that of GT image is less than one pixel difference for normal and abnormal cases.

Due to the ambiguous nature of breast thermograms, writing a generalized algorithm for automatic segmentation is a tedious work. In this article, by making use of shape feature of breasts, we are able to detect ROI of breast satisfactorily. Also by applying polynomial curve fitting on inframammary curves, bifurcation lines are detected accurately. For lateral and upper border detection, breast shape should have at least slight concavity in upper part of the breast and convexity in the lower part of the breast. Figure 4 shows segmentation results obtained for some of the small, medium, large and asymmetric breast cases present in the image database [24,28]. The proposed algorithm for segmentation works faster in comparison with the most commonly used Hough transform method for curve extraction. As discussed in section-related work, in order to extract the feature curves of the breast thermogram image Hough transform was used in [7,20,25] by detecting parabolic curves. Detection of parabolic curves requires 3D accumulator array in any orientation. Due to this, the computational complexity involved in the segmentation of breast thermogram image using Hough transform method is greater than $O(MN)$ for an image of size $(M \times N)$ and also it grows exponentially with increase in number of parameters. In the proposed algorithm, we search for two longer curves (infra mammary) in the lower half of the image, which are projecting towards centre, by boundary tracing. Polynomial curve fitting is applied on detected infra mammary curves and extended upwards to find the bifurcation point. The worst case time complexity of the proposed method is less than $O(MN/2)$ in detection of infra mammary curves.

Table 1 Mean ± SD of MSE, PSNR, JC and ED measurements

Sl. no.	Parameters	Normal breast	Abnormal breast
1	MSE	0.022 ± 0.001	0.050 ± 0.071
2	PSNR	17.4 ± 0.31	15.6 ± 0.85
3	JC	0.978 ± 0.01	0.963 ± 0.03
4	ED	0.95 ± 0.48	0.964 ± 0.49

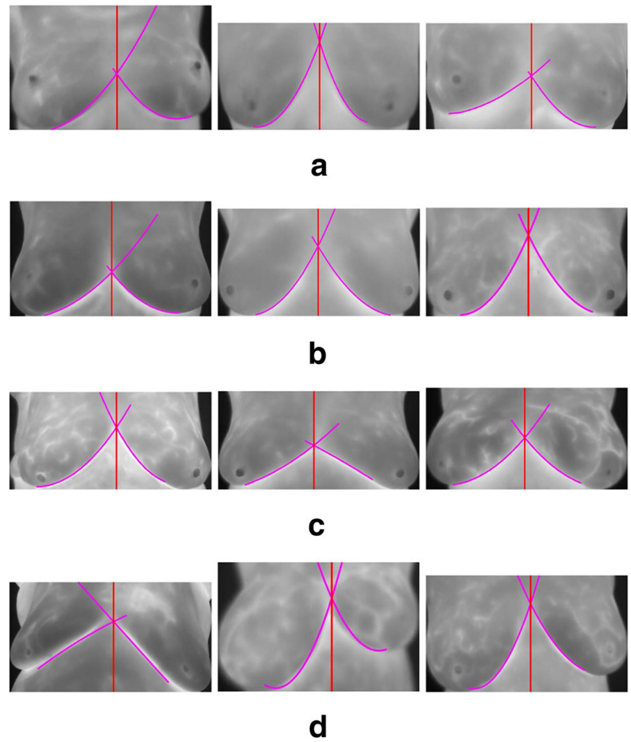

Fig. 4 Segmentation results for different sizes and shapes of breasts. **a** Small breasts, **b** medium breasts, **c** large breasts, **d** asymmetric breasts

Feature extraction is second important phase in the analysis of breast thermograms. The intensity variation of thermogram image depends on thermal energy distribution in respective areas as different textures. Success of CAD relies strongly on effective feature extraction. A good quality feature set must contain relevant information of the image and compact in structure. Statistical analysis of extracted features is shown in Table 2. From Table 2, it is observed that, mean ± SD for each feature is high for abnormal breasts compared to normal breasts because of asymmetry in abnormal images. Figure 5 gives the plot of comparison of feature values for highly significant features(t value >5) on normal and abnormal breast thermogram images. From the statistical

Table 2 Statistical analysis of extracted features

Features	Normal breast		Abnormal breast		*p* value	*t* value
	Mean	SD	Mean	SD		
Histogram						
Mean	**0.0993**	**0.0803**	**0.2651**	**0.2133**	**0.000016**	**4.6005**
Variance	0.2204	0.1590	0.3020	0.2538	0.088698	1.7238
Skewness	**0.1362**	**0.1358**	**0.3049**	**0.2874**	**0.001219**	**3.3572**
Kurtosis	**0.0955**	**0.0755**	**0.3493**	**0.2458**	**0.000000**	**6.2445**
Entropy	**0.1363**	**0.0930**	**0.3805**	**0.2638**	**0.000000**	**5.5229**
GLCM features						
Mean	0.1897	0.0972	0.2505	0.1815	0.065502	1.8681
Variance	**0.2204**	**0.1428**	**0.5320**	**0.3056**	**0.000000**	**5.8422**
Entropy	0.2566	0.1066	0.3177	0.2250	0.124327	1.5536
Contrast	0.0942	0.0583	0.1295	0.1524	0.174621	1.3700
Correlation	**0.1936**	**0.1500**	**0.2880**	**0.2524**	**0.045309**	**2.0344**
Energy	**0.1341**	**0.0875**	**0.3876**	**0.2627**	**0.000000**	**5.7905**
Homogeneity	0.1095	0.0661	0.1498	0.1515	0.127028	1.5424

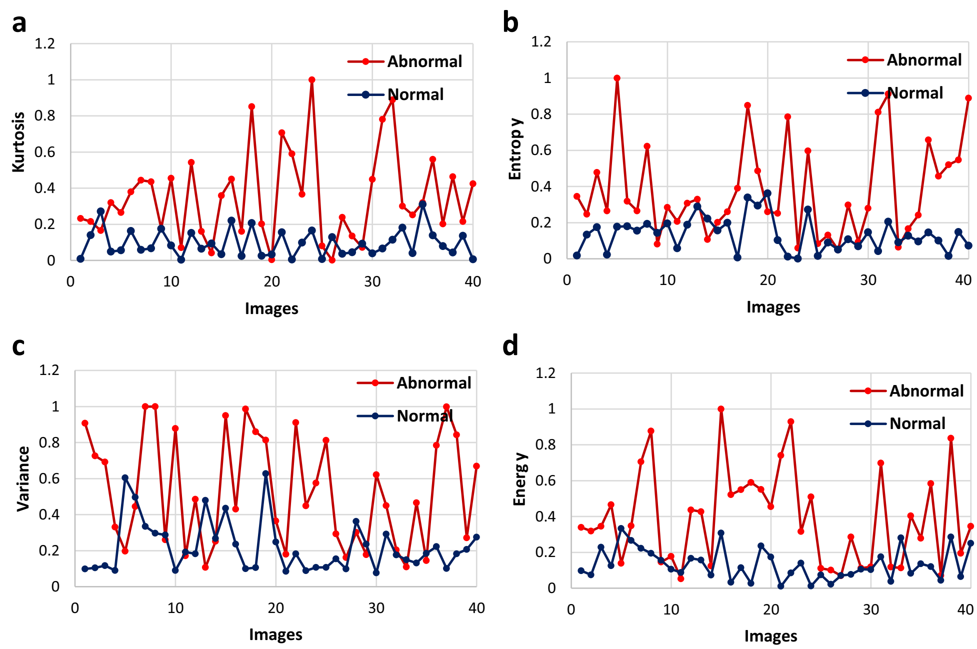

Fig. 5 Plot of comparison of features ($t > 5$) on normal and abnormal thermograms: **a** kurtosis, **b** entropy, **c** GLCM variance, **d** GLCM energy

test, we find that absolute difference of histogram extracted mean, skewness, kurtosis, entropy and GLCM extracted variance, correlation and energy are significant in detection of breast cancer and are highlighted in bold face in Table 2.

Table 3 presents the performance of SVM classifier with linear, RBF, polynomial, quadratic and MLP kernels. From Table 3, it is observed that RBF and polynomial kernels performed better in comparison with other kernel functions and are highlighted. We are able to get an accuracy of 90%, sensitivity of 87.5% and specificity of 92.5% with SVM RBF classifier.

Table 3 Classifier performance on significant features

Classifier	Accuracy	Sensitivity	Specificity
SVM			
Linear	88.75	82.5	95
RBF	**90**	**87.5**	**92.5**
Polynomial	**90**	**82.5**	**97.5**
Quadratic	88.75	80	97.5
MLP	83.75	85	82.5

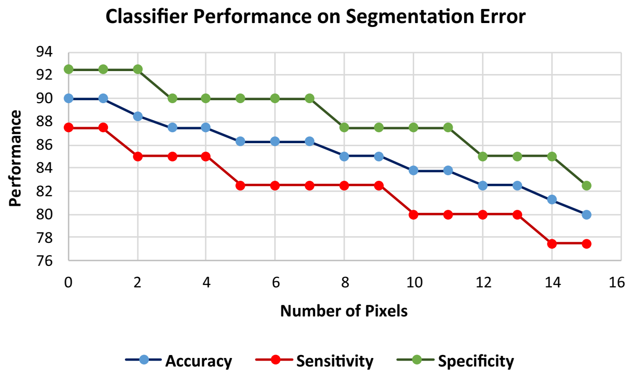

Fig. 6 Classifier performance on segmentation error

Performance of the classifier against small errors in segmentation is tested by introducing errors in the bifurcation line. Bifurcation line is shifted by one pixel at a time by keeping the data, feature set and classifier (SVM RBF) unchanged. Algorithm is tested for fifteen times. Figure 6 depicts the plot of classifier performance against segmentation errors. Accuracy of classification slowly reduces, when the segmentation error increases and remains almost constant for one or two pixel shifts of bifurcation line. Similarly sensitivity and specificity reduces as the error increases. For a shift of fifteen pixels the accuracy of classification falls by 10%. In manual or semi-automated segmentation methods, these minute shifts may not be noticeable and leads to misclassification.

Summary of similar methods for classification of breast cancer using breast thermogram images is shown in Table 4. Classifier performance is compared between proposed segmentation and most commonly used Hough Transform [7,25] method by keeping dataset, features [histogram and GLCM (average in four directions)] and classifier(SVM RBF) unchanged and results are shown in Table 5. We have obtained better accuracy of 90%, sensitivity of 87.5% and specificity of 92.5% in comparison with the Hough Transform method of segmentation and are highlighted in Table 5.

5 Conclusion

The accuracy of CAD system for breast thermography mainly depends on appropriate segmentation and extraction of relevant features. This article proposed a novel algorithm for fully automatic segmentation of breast thermograms. Segmentation results are validated with their Ground Truths. An average mean square error and Jaccard coefficient of 0.036 and 0.97 are obtained for the dataset of normal and abnormal thermograms. The error in detection of bifurcation line is less than one pixel. Statistical texture features are extracted by computing histogram and GLCM. Mean, skewness, kurtosis, entropy, GLCM variance, GLCM correlation and GLCM

Table 4 Summary of similar studies on breast thermogram images

Authors	Segmentation	Features/ Classifier	Number of patients	Performance
Schafer et al. [27]	Manual	Statistical features/fuzzy classifier	146 (29 malignant, 117 benign)	Accuracy: 80%
Araujo et al. [3]	Semi-automated	Interval symbolic feature extraction on temperature values/distance-based classifier	50 (14 malignant, 19 benign, 17 cyst)	Sensitivity: 85.7%; specificity: 86.5%
Borchart et al. [7]	Segmentation based on threshold, edge-based techniques and Hough transform	Statistical temperature features/SVM classifier	28 (24 abnormal, 4 normal)	Accuracy: 85.7%; sensitivity: 95.83%; specificity: 25%
Acharya et al. [1]	Manual	Texture features from co-occurrence matrix and run length matrix/SVM classifier	50 (25 normal, 25 cancerous)	Accuracy: 88.10%; sensitivity: 85.71%; specificity: 90.48%
Qi et al. [25]	Canny edge detection and Hough transform	Statistical texture features/*k*-means and kNN	24 (6 normal, 18 cancerous)	Not specified
Nicandro et al. [22]	Not specified	Temperature features/Naive Bayes classifier	98 (77 malignant, 21 healthy)	Accuracy: 71.88%; sensitivity: 82%; specificity: 37%
Ali et al. [5]	Segmentation based on distance between camera and patient	Statistical/ SVM quadratic	63 (29 healthy, 34 malignant)	Average accuracy of 4 scenarios: 74.5%
Gaber et al. [11]	Neutrosophic sets and fast fuzzy C means	Gabor coefficients statistical/SVM RBF	63 (29 healthy, 34 malignant)	Average accuracy of 4 scenarios: 88.41%

Table 5 Classifier performance using Hough transform and proposed segmentation method

Segmentation	Accuracy	Sensitivity	Specificity
Hough transform	76.25	75	77.5
Proposed method	**90**	**87.5**	**92.5**

energy are found to be highly significant in the detection of breast cancer. We have obtained an accuracy of 90% in classifying normal versus abnormal breasts by using SVM RBF and SVM polynomial classifiers.

References

1. Acharya, U.R., Ng, E.Y.K., Tan, J.H., Sree, S.V.: Thermography based breast cancer detection using texture features and support vector machine. J. Med. Syst. **36**(3), 1503–1510 (2012)
2. Arakeri, M.P., Reddy, G.R.M.: Computer-aided diagnosis system for tissue characterization of brain tumor on magnetic resonance images. SIViP **9**(2), 409–425 (2015)
3. Araujo, M.C., Lima, R.C., de Souza, R.M.: Interval symbolic feature extraction for thermography breast cancer detection. Expert Syst. Appl. **41**(15), 6728–6737 (2014)
4. Araujo, M.C.D., Lima, R.D.C.F.D., Magnani, F.S., da Silva, R.N.T., dos Santos, F.G.: The use of a database as an auxiliar tool in thermographic diagnosis for early detection of breast diseases. In: 12th Brazilian Congress of Thermal Engineering and Sciences, Belo Horizonte, MG. Proceedings of ENCIT 2008, ABCM (2008)
5. A.S.Ali, M., nad Tarek Gaber, G.I.S., Hassanien, A.E., Snasel, V., Silva, L.F.: Detection of breast abnormalities of thermograms based on a new segmentation method. In: Proceedings of the Federated Conference on Computer Science and Information Systems (FedCSIS), vol. 5, pp. 255–261 (2015). doi:10.15439/2015F318
6. Borchartt, B., Concia, T., Limab, R.C.F., Resminia, R., Sanchez, A.: Breast thermography from an image processing view point: a survey. Int. J. Signal Process. **93**(10), 2785–2803 (2013)
7. Borchartt, T.B., Resmini, R., Conci, A.: Thermal feature analysis to aid on breast disease diagnosis. In: 21st Brazilian Congress of Mechanical Engineering Natal RN, Brazil. Proceedings of COBEM, ABCM, pp. 24–28 (2011)
8. Crum, W.R., Camara, O., Hill, D.L.G.: Generalized overlap measures for evaluation and validation in medical image analysis. IEEE Trans. Med. Imaging **25**(11), 1451–1461 (2006)
9. EtehadTavakol, M., Chandran, V., Ng, E., Kafieh, R.: Breast cancer detection from thermal images using bispectral invariant features. Int. J. Thermal Sci. **69**(1), 21–36 (2013)
10. EtehadTavakol, M., NG, E.Y.K.: Breast thermography as a potential non-contact method in the early detection of cancer: a review. J. Mech. Med. Biol. **13**(2), 133,000 (2013)
11. Gaber, T., Ismail, G., Anter, A., Soliman, M., Ali, M., Semary, N., Hassanien, A.E., Snasel, V.: Thermogram breast cancer prediction approach based on neutrosophic sets and fuzzy c-means algorithm. In: 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 4254–4257 (2015)
12. Khan, N.M., Ksantini, R., Ahmad, I.S., Guan, L.: SN-SVM: a sparse nonparametric support vector machine classifier. SIViP **8**(8), 1625–1637 (2014)
13. Krawczyk, B., Schaefer, G.: A hybrid classifier committee for analysing asymmetry features in breast thermograms. Appl. Soft Comput. **20**(Special issue), 112–118 (2014)
14. Lago, M., Ruprez, M., Martnez-Martnez, F., Martnez-Sanchis, S., Bakic, P., Monserrat, C.: Methodology based on genetic heuristics for in-vivo characterizing the patient-specific biomechanical behavior of the breast tissues. Expert Syst. Appl. **42**(21), 7942–7950 (2015)
15. Lee, H., Chen, Y.P.P.: Image based computer aided diagnosis system for cancer detection. Expert Syst. Appl. **42**(12), 5356–5365 (2015)
16. Lee, J., Chen, S., Reece, G.P., Crosby, M.A., Beahm, E.K., Markey, M.K.: A novel quantitative measure of breast curvature based on catenary. IEEE Trans. Biomed. Eng. **59**(4), 1115–1124 (2012)
17. Lipari, C.A., Head, J.: Advanced infrared image processing for breast cancer risk assessment. In: Proceedings of the 19th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Chicago, vol. 2, pp. 673–676 (1997)
18. Mallucci, P., Branford, O.: Concepts in aesthetic breast dimensions analysis of the ideal breast. J. Plast. Reconstr. Aesthet. Surg. **65**(1), 8–16 (2012)
19. Moghbel, M., Mashohor, S.: A review of computer assisted detection/diagnosis (CAD) in breast thermography for breast cancer detection. Artif. Intell. Rev. **39**(4), 305–313 (2013)
20. Moghbel, M., Mashohor, S., ah Rozi Mahmud, H., Saripan, M.I.B.: Random walkers based segmentation method for breast thermography. In: IEEE EMBS International Conference on Biomedical Engineering and Sciences Langkawi, pp. 627–630 (2012)
21. Motta, L.S., Conci, A., Lima, R.C.F., Diniz, E.M.: Automatic segmentation on thermograms in order to aid diagnosis and 2d modelling. In: Proceedings of 10th Workshop em Informatica Medica, Brazil, vol. 1, pp. 1610–1619 (2010)
22. Nicandro, C.R., Efren, M.M., Yaneli, A.A., Enrique, M.D.C.M., Gabriel, A.M.H., Nancy, P.C., Alejandr, G.H., de Jesus, H.R.G., Rocio, B.M.: Evaluation of the diagnostic power of thermography in breast cancer using bayesian network classifiers. Comput. Math. Methods Med. **2013**(5), 1–10 (2013)
23. Daisy, P.A., Nagappa, A.N., Udupa, N., Mathew, N., Carla, B.: Effectiveness of a planned teaching program on improving the knoweldge on warning signs, risk factors and early detection methods. Indian J. Pharm. Pharmacol. **2**(1), 6–9 (2015)
24. PROENG: image processing and image analysis applied to mastology. Available at http://visual.ic.uff.br/en/proeng/. Last Accessed on 5th Oct. 2015
25. Qi, H., Snyder, W.E., Head, J.F., Elliott, R.L.: Detecting breast cancer from infrared images by asymmetry analysis. In: Engineering in Medicine and Biology Society Proceedings of the 22nd Annual International Conference of the IEEE , Chicago, vol. 2, pp. 1227–1228 (2000)
26. Sathish, D., Kamath, S., Rajagopal, K.V., Prasad, K.: Medical imaging techniques and computer aided diagnostic approaches for the detection of breast cancer with an emphasis on thermography a review. Int. J. Med. Eng. Inform. **8**(3), 275–299 (2016)
27. Schaefera, G., Zavisek, M., Nakashima, T.: Thermography based breast cancer analysis using statistical features and fuzzy classification. Pattern Recogn. **47**(6), 1133–1137 (2009)
28. Silva, L.F., Saade, D.C.M., Sequeiros, G.O., Silva, A.C., Paiva, A.C.: A new database for breast research with infrared image. J. Med. Imaging Health Inform. **4**(1), 92–100 (2014)
29. de Souza Marques, R.: Automatic Segmentation of the Breasts in Thermal Imaging. Master's thesis, Niteri, RJ (2012)
30. Tan, T.Z., Quek, C., Ng, G., Ng, E.: A novel cognitive interpretation of breast cancer thermography with complementary learning fuzzy neural memory structure. Expert Syst. Appl. **33**(3), 652–666 (2007)
31. Walker, D., Kaczor, T.: Breast thermography: history, theory, and use. Nat. Med. **4**(7) (2012). Available at http://www.naturalmedicinejournal.com. Last accessed on 6th Sept 2016