Texture analysis of breast thermograms using neighbourhood grey tone difference matrix

Dayakshini Sathish and Surekha Kamath*

ICE Department, Manipal Institute of Technology, Manipal University, Manipal 576104, Karnataka, India
Email: dayakshini@gmail.com
Email: surekha.kamath@manipal.edu
*Corresponding author

Keerthana Prasad

School of Information Sciences Manipal, Manipal University, Manipal 576104, Karnataka, India
Email: keerthana.prasad@manipal.edu

Rajagopal Kadavigere

Kasturba Medical College Manipal, Manipal University, Manipal 576104, Karnataka, India
Email: rajagopalkv@yahoo.com

Abstract: Breast cancer is the leading cancer in women worldwide. Early detection can reduce the mortality rate of breast cancer. Breast thermography is a non-invasive and simple imaging technique used for early detection of breast cancer. Feature extraction and selection of appropriate features play a major role in computer-aided detection of breast cancer using breast thermograms. In this article, texture features are extracted from automatically segmented breast thermograms by computing neighbourhood grey tone difference matrix (NGTDM) and run length matrix (RLM). Significance of these features in differentiating the abnormal breast from the normal breast is found by statistical test. NGTDM extracted coarseness, busyness, complexity, strength and RLM extracted long run emphasis and run percentage are found to be significant by statistical test. Extracted features are computationally less expensive and attained an average accuracy of 80%, sensitivity of 94% and specificity of 71.4% using back propagation neural network classifier.

Keywords: asymmetry analysis; breast cancer; breast thermography; neighbourhood grey tone difference matrix; statistical test.

1 Introduction

Breast cancer is the most commonly diagnosed cancer in women worldwide and accounting for 23% of total cancer cases (Jemal et al., 2011). Mortality rate of cancer can be reduced, if cancer is detected and treated early. Breast thermography can be used as an adjunct screening tool for early detection of breast cancer (Acharya et al., 2014; EtehadTavakol et al., 2013). It is a painless, non-invasive, low cost screening test and can be used for women of all ages particularly women having dense breast, where mammography is less effective (American College of Clinical Thermology, 2015). Breast thermography is based on infrared radiation of bodies with temperatures higher than absolute zero (Lahiri, 2012). Due to the higher metabolic activity and angiogenesis surrounding the cancerous tissue, the precancerous and cancerous tissue has higher temperature in comparison to normal tissue (Lee and Chen, 2015). Cancerous tumours rarely grow symmetrically in right and left breast, so physicians, normally use asymmetry analysis for interpreting breast thermograms (Borchartt et al., 2013; Qi et al., 2000).

Many researchers are working on computer-aided detection (CAD) of breast cancer using breast thermograms to extract more information from the thermograms and to
automate the process of detection. Extraction and selection of appropriate features are very essential to improve the classifier performance in classifying normal and abnormal breast in CAD (Borchartt et al., 2013; Sathish et al., 2016).

2 Related work

Krawczyk and Schaefer (2014) and Schaefera et al. (2009) extracted various features namely, basic statistical, moment, cross cooccurrence, mutual information and Fourier descriptor based features from the manually segmented left and right breast thermogram images. The extracted features were fed to fuzzy classification system and obtained an accuracy of classification of 80%. Borchartt et al. (2011) used range of temperature in region of interest (ROI), the mean temperature, standard deviation and quantisation of the higher tone in an eight level posterization. These features were extracted from the entire breast image and breast quadrants. Support vector machine (SVM) classifier provided an accuracy of classification around 86%. Acharya et al. (2012) extracted texture features from cooccurrence matrix and run length matrix (RLM). SVM classifier was used for automatic classification of normal and malignant breast conditions. They obtained an accuracy of 88.10%, sensitivity and specificity of 85.71 and 90.48%, respectively, for a set of 50 thermograms. Nicandro et al. (2013) extracted different types of features using the temperature variations of breast namely, temperature difference between left and right breast, number of veins with highest temperature, heat area under the breast, amount of hottest points, geometry of the hot centre, histogram and age of the patient. Bayesian network classifier was used for classification and obtained an accuracy of 74%. Milosevic et al. (2014) computed features based on grey level cooccurrence matrix (GLCM). A total of twenty features were extracted from thermograms. Three types of classifiers namely, SVM, Naïve Bayes and K-nearest neighbour (KNN) classifier were used. Classification performance was evaluated by fivefold cross-validation and receiver operating characteristic analysis. KNN classifier performed better than SVM and Bayes. Ali et al. (2015) extracted first-order statistical and GLCM-based features from the automatically segmented ROI. SVM with various kernel functions was used to detect the normal and abnormal breast. They analysed the accuracy of classifier results by using four types of scenarios. Each scenario had different number of images for training and testing. From their results, we find that first scenario (19 normal, 24 abnormal samples for training and 10 normal, 10 abnormal samples for testing) performed better than other scenarios. Accuracy of 85% was obtained by quadratic and linear kernels for statistical features and for GLCM-based features quadratic and polynomial kernel gave an accuracy of 80%.

From the literature survey as discussed above, it is observed that researchers have extracted spatial based statistical features (Acharya et al., 2012; Ali et al., 2015; Borchartt et al., 2011; Krawczyk and Schaefer, 2014; Milosevic et al., 2014; Nicandro et al., 2013; Schaefera et al., 2009) and spectral based features (Krawczyk and Schaefer, 2014; Schaefera et al., 2009). In the proposed work, texture features are extracted from the spatial domain, which are correlated with human perception of textures. Neighbourhood grey tone difference matrix (NGTDM) measures the grey scale difference between the neighbouring pixels. Grey levels of abnormal breast vary very frequently in comparison with the normal breast due to the variation in temperature of that surface. NGTDM represents the intensity variation in breast thermogram image in a compact form, since it
Texture analysis of breast thermograms

is a column matrix. We also computed RLM based features in four directions to extract the directional information of the image.

3 Materials and methods

Breast thermogram images used in this work are collected from the public database at visual lab, Fluminense Federal University, Brazil (PROENG, 2015). One hundred breast thermogram temperature images (53 normal and 47 abnormal cases) are considered for the study. Breast thermogram images were captured using FLIR infra-red camera with a temperature sensitivity of 0.04°C. The resolution of the image is 640 × 480 pixels. The population has a set of patients with confirmed tumour by clinical exam, ultrasound, mammography and biopsy exams (De Araujo et al., 2008; Silva et al., 2014).

Breast thermogram images are segmented automatically to separate right and left breast for asymmetry analysis (Sathish et al., 2017). ROI of the breast is segmented from the background by applying Canny edge detection on the image to extract outer edges of the image. Shape features of the breast (Mallucci and Branford, 2012) are used to locate lateral, upper and lower boundaries of ROI. Infra mammary curves are detected and polynomial curve fitting is applied to find the bifurcation line to separate right and left breast for asymmetry analysis (Sathish et al., 2014, 2015). Texture features are extracted from both right and left breast using NGTDM and run length matrices. Asymmetry between right and left breast is measured by computing the absolute difference between feature values of right and left breast. The significance of these feature values in detection of breast cancer is found by statistical analysis. Finally, significant features are selected and used for training and testing the classifiers. The block diagram of the proposed method is shown in Figure 1.

Figure 1  Block diagram representation of the proposed work (see online version for colours)

3.1 NGTDM features

NGTDM reflects a grey scale difference between pixels with certain grey scale and their neighbouring pixels. It measures textures correlated with human perception. The entries of a NGTDM matrix are computed based on measuring the difference between the intensity level of a pixel and the average intensity computed over a square sliding window centred at the pixel. The various textures extracted from NGTDM are coarseness, contrast, complexity, busyness (fineness) and texture strength. NGTDM is a column matrix and defined as follows (Amadasun and King, 1989):
Let $f(k,l)$ be the grey tone of any pixel at $(k,l)$. Then average grey tone over a
neighbourhood centred at $(k,l)$ (excluding $(k,l)$) is defined as:

$$\bar{A} = \bar{A}(k,l) = \frac{1}{w-1} \left[ \sum_{m=-d}^{d} \sum_{n=-d}^{d} f(k+m,l+n) \right]; (m,n) \neq (0,0)$$  \hspace{1cm} (1)

where $d$ specifies neighbourhood size and

$$w = (2d + 1)^2$$  \hspace{1cm} (2)

Then the $i$th entry in NGTDM is

$$s(i) = \left\{ \begin{array}{ll}
\sum_{j=0}^{G_{i}} j \bar{A} & \text{for } i \in N_i; \text{ if } N_i \neq 0 \\
0, & \text{otherwise}
\end{array} \right.$$  \hspace{1cm} (3)

where $N_i$ is set of all pixels having grey tone $i$, except in the peripheral regions of width
$d$. For example, NGTDM calculation of $5 \times 5$ sample image is shown in Figure 2 for a
distance $d = 1$ (3 × 3 neighbourhood). This neighbourhood can only be centred on pixels
within the shaded square. Texture features extracted from the NGTDM are defined as
follows (Amadasun and King, 1989):

1. **Coarseness**
   
   $$\varepsilon = \left(\epsilon + \sum_{i=0}^{G_i} P_i s(i)\right)^{-1}$$  \hspace{1cm} (4)

   where $G_i$ the highest grey tone value present in the image and $\epsilon$ is the small number to
   prevent coarseness to infinite. For $N \times N$ image, $P_i$ is the probability of occurrence of
grey tone value $i$ and

   $$P_i = \frac{N_i}{n^2}, \text{ where } n = N - 2d$$  \hspace{1cm} (5)

2. **Contrast**
   
   $$\text{Contrast} = \frac{1}{N_g(N_g - 1)} \sum_{i=0}^{G_i} \sum_{j=0}^{G_i} P_i P_j (i-j)^2 \left[ \frac{1}{n^2} \sum_{i=0}^{G_i} s(i) \right]$$  \hspace{1cm} (6)

   where $N_g$ is the total number of different grey levels present in the image.

3. **Busyness**
   
   $$\text{Busyness} = \frac{\sum_{i=0}^{G_i} P_i s(i)}{\sum_{i=0}^{G_i} \sum_{j=0}^{G_i} (P_i - j P_j)}$$  \hspace{1cm} (7)

4. **Complexity**
   
   $$\text{Complexity} = \sum_{i=0}^{G_i} \sum_{j=0}^{G_i} \frac{1}{n^2 (P_i + P_j)} \left\{ P_i s(i) + P_j s(j) \right\}$$  \hspace{1cm} (8)

5. **Strength**
   
   $$\text{Strength} = \left[ \sum_{i=0}^{G_i} \sum_{j=0}^{G_i} (P_i + P_j) (i-j)^2 \right] \left[ \epsilon + \sum_{i=0}^{G_i} s(i) \right]$$  \hspace{1cm} (9)
Texture analysis of breast thermograms

Figure 2  Example for NGTDM

\[
\begin{array}{cccc}
1 & 1 & 4 & 3 & 1 \\
3 & 4 & 0 & 1 & 1 \\
5 & 4 & 2 & 2 & 2 \\
2 & 1 & 1 & 4 & 4 \\
0 & 2 & 2 & 5 & 1 \\
\end{array}
\]

(a) Sample image  \hspace{1cm} (b) NGTDM values

Note: NGTDM, Neighbourhood grey tone difference matrix

where \( P \neq 0 \) and \( P \neq 0 \) for Eqs. (7)–(9).

In the proposed method, we have computed NGTDM features for \( d = 1 \) (3 × 3 neighbourhood) and \( d = 2 \) (5 × 5 neighbourhood).

3.2 RLM-based features

We have extracted RLM-based features to find the local intensity variations of breast thermogram image. Since the cancerous tumours can grow in any direction, proposed method computed the RLM in 0°, 45°, 90° and 135° directions. From all the RLMs, various features are extracted. Final feature set of RLMs are derived by computing average of each feature in four directions of all samples.

A grey level run is a set of successive, collinear pixels having the same grey level value. The length of the run is the number of pixels in the run (Acharya et al., 2012; Galloway, 1975; Tang, 1998; Liu et al., 2012). Figure 3 shows the computation of RLMs for an image matrix of size 4 × 4 with four intensity levels for horizontal (0°) and right diagonal (45°) directions. RLM \( p(i,j) \) is defined as the number of runs with pixels of grey level \( i \) and run length \( j \). Let \( N_g \) be the number of grey levels in the image. \( N_r \) be the number of different run lengths and \( P \) be the number of pixels present in the image. From each run-length matrix \( p(i,j) \), we have computed statistical measures namely, short run emphasis (SRE), long run emphasis (LRE), grey level non-uniformity (GLN), run length non-uniformity (RLN) and run length percentage (RP). These features are defined as follows (Sonka, 2004; Galloway, 1975):

\[
SRE = \frac{\sum_{i=1}^{N_g} \sum_{j=1}^{N_r} \frac{p(i,j)}{j^2}}{\sum_{i=1}^{N_g} \sum_{j=1}^{N_r} p(i,j)}
\]

SRE is computed by dividing each run length value by the length of the run squared. This tends to emphasise short runs. The denominator is the total number of runs in the image and serves as a normalising factor.
D. Sathish et al.

Figure 3 Example for run length matrix

\[
\begin{array}{cccc}
0 & 1 & 2 & 3 \\
0 & 2 & 3 & 3 \\
2 & 1 & 1 & 1 \\
3 & 0 & 3 & 0 \\
\end{array}
\quad
\begin{array}{cccc}
\text{Grey level} & \text{Runs} \\
0 & 1 & 2 & 3 & 4 \\
0 & 4 & 0 & 0 & 0 \\
1 & 1 & 0 & 1 & 0 \\
2 & 3 & 0 & 0 & 0 \\
3 & 3 & 1 & 0 & 0 \\
\end{array}
\quad
\begin{array}{cccc}
\text{Grey level} & \text{Runs} \\
0 & 1 & 2 & 3 & 4 \\
0 & 4 & 0 & 0 & 0 \\
1 & 4 & 0 & 0 & 0 \\
2 & 0 & 0 & 1 & 0 \\
3 & 3 & 1 & 0 & 0 \\
\end{array}
\]

(a) Image (b) RLM at 0º (c) RLM at 45º

2 \text{LRE} = \frac{\sum_{i=1}^{N_x} \sum_{j=1}^{N_y} r(i,j)^2 p(i,j)}{\sum_{i=1}^{N_x} \sum_{j=1}^{N_y} p(i,j)} \quad (11)

LRE is computed by multiplying each run length value by the length of the run squared. This highlights long runs. The denominator is a normalising factor.

3 \text{GLN} = \frac{\sum_{i=1}^{N_x} \left( \sum_{j=1}^{N_y} p(i,j) \right)^2}{\sum_{i=1}^{N_x} \sum_{j=1}^{N_y} p(i,j)} \quad (12)

GLN value is low, if the runs are equally distributed throughout the grey levels.

4 \text{RLN} = \frac{\sum_{i=1}^{N_x} \left( \sum_{j=1}^{N_y} p(i,j) \right)^2}{\sum_{i=1}^{N_x} \sum_{j=1}^{N_y} p(i,j)} \quad (13)

If the runs are equally distributed throughout the lengths, RLN will have a low value.

5 \text{RP} = \frac{\sum_{i=1}^{N_x} \sum_{j=1}^{N_y} p(i,j)}{P} \quad (14)

RP is a ratio of the total number of runs to the total number of possible runs, if all runs had a length of one. RP value will be low for linear structures.

3.3 Asymmetry measurement and statistical test

To measure the asymmetry between right and left breast, absolute difference of each feature value between right and left breast is computed. Table 1 shows the computation of asymmetry measure for NGTDM and RLM features. Asymmetry measured values are normalised and feature database is created.
Table 1  Asymmetry measure of features

<table>
<thead>
<tr>
<th>Feature</th>
<th>Features extracted from right breast</th>
<th>Features extracted from left breast</th>
<th>Asymmetry measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>NGTDM Coarseness (CR)</td>
<td>CR_R</td>
<td>CR_L</td>
<td></td>
</tr>
<tr>
<td>Contrast (CT)</td>
<td>CT_R</td>
<td>CT_L</td>
<td></td>
</tr>
<tr>
<td>Busyness (BS)</td>
<td>BS_R</td>
<td>BS_L</td>
<td></td>
</tr>
<tr>
<td>Complexity (CP)</td>
<td>CP_R</td>
<td>CP_L</td>
<td></td>
</tr>
<tr>
<td>Strength (ST)</td>
<td>ST_R</td>
<td>ST_L</td>
<td></td>
</tr>
<tr>
<td>RLM</td>
<td>SRE_R</td>
<td>SRE_L</td>
<td></td>
</tr>
<tr>
<td>LRE</td>
<td>LRE_R</td>
<td>LRE_L</td>
<td></td>
</tr>
<tr>
<td>GLN</td>
<td>GLN_R</td>
<td>GLN_L</td>
<td></td>
</tr>
<tr>
<td>RLN</td>
<td>RLN_R</td>
<td>RLN_L</td>
<td></td>
</tr>
<tr>
<td>RP</td>
<td>RP_R</td>
<td>RP_L</td>
<td></td>
</tr>
</tbody>
</table>

NGTDM, Neighbourhood grey tone difference matrix; RLM, run length matrix; SRE, short run emphasis; LRE, long run emphasis; GLN, grey level non-uniformity; RLN, run length non-uniformity; RP, run length percentage

Statistical significance of each feature in differentiating the normal and abnormal breasts is found by conducting an independent t test. Independent t test indicates, whether or not the difference between two group’s averages most likely reflects a real difference in the population from which the groups are sampled. The significance level is tested at 5% by assuming equal variances. Highly significant features are selected for training and testing the classifiers.

3.4 Classification

Artificial neural network (ANN) and SVM are used classification of breast thermograms as normal and abnormal cases. ANNs are the important data mining tools used for classification. Basic neural network is composed of three layers, input, output and hidden layer. Each layer can have number of nodes and nodes from input layer are connected to the nodes from hidden layer. Nodes from hidden layer are connected to the nodes from output layer. Those connections represent weights between nodes (Duda et al., 2002; Sivanandam and Deepa, 2007). One of the most popular ANN algorithm is back propagation algorithm. In back propagation algorithm, the neural network is trained on the training set of the data such that the weights get updated recursively with respect to the patterns. This is also an optimisation problem where following objective function is minimised (Martis et al., 2014).

\[ J(w) = \frac{1}{2} \sum_{n=1}^{N} \sum_{k=1}^{C} (y_k(x_n,w) - t^*_k)^2 \]  

(15)

where \( y_k(x_n,w) \) is the network response for kth class neuron in the output layer and \( t^*_k \) is the target for class k of nth observation feature vector. The gradient descent method is
used in the analysis to adapt the network weights. Once the network is trained, the test signal is fed to the neural network and the data are classified to one of the two predefined classes. The proposed method uses three-layer back propagation neural network. The first layer uses tangent sigmoid transfer function and the second layer uses linear transfer function.

SVM is the popular and most important technique of classification and was developed by Vladimir Vapnik (Duda et al., 2002). It is based on statistical learning theory. SVM is called as maximum margin classifier, because it simultaneously minimise the empirical classification error and maximises the geometric margin of the separating hyperplane. The decision function is fully specified by a subset of training samples the support vectors (Martis et al., 2014; Duda et al., 2002). Any point x lying on the separating hyperplane satisfies

\[ w^T x + b = 0 \]  

\( w \) is the vector normal to the plane, and \( b \) is a constant that describes how much the plane is shifted relative to the origin. The distance of the plane from the origin is:

\[ \frac{b}{\|w\|} \]  

Parallel lines are drawn on either side of the decision boundary with the decision boundary as the median. The margin \( m = d_+ + d_- \) is restricted by the data points closest to the boundary. The decision boundary should classify all points correctly as:

\[ y_i (w^T x_i + b) > 1, \text{ for all } i \]  

The decision boundary can be found by solving the following constrained optimisation problem as

\[ \frac{1}{2} \|w\|^2 \]  

To avoid the increased computational complexity and curse of dimensionality, a kernel trick or kernel function employed, which computes an equivalent kernel value in the input space such that no explicit mapping is required. The proposed method uses SVM classifier with various kernel functions namely, quadratic, polynomial and Gaussian kernels to classify the data points and back propagation neural network with three hidden layers. \( K \)-fold cross-validation with \( K = 10 \) is used in order to reduce the bias in choosing training and testing sets for classification.

### 3.5 Algorithm of proposed method

The algorithm of the proposed method is as follows:

**Algorithm:**

a. Segment the ROI of right and left breast.

b. Compute NGTDM of right and left breast thermogram image separately for 3 × 3 neighborhood (\( d = 1 \)).
c. Compute coarseness (CR), contrast (CT), busyness (BS), complexity (CP) and strength (ST) from each NGTDM.

d. Compute the absolute difference of each NGTDM feature values between right and left breast.

e. Repeat the steps b to d for 5 × 5 neighborhood (d = 2).

f. Compute RLM of right and left breast thermogram image separately in horizontal direction.

g. Compute SRE, LRE, GLN, RLN and RP from each RLM.

h. Compute the absolute difference of each RLM feature values between right and left breast.

i. Repeat the steps f to h for vertical, left diagonal and right diagonal directions.

j. Find the average of each feature of RLM in four directions.

k. Normalize all the values obtained by step d and j for individual features.

l. Create feature database for normalized features.
m. Conduct independent t test to find the significant features from feature database.

n. Train and Test the SVM and ANN classifier using significant features.
o. Compute the average performance of the classifiers using k fold cross validation.

4 Results and discussion

Statistical test is conducted on features to find the significant features. Features extracted from NGTDM such as coarseness, busyness, complexity and strength are found to be significant in describing asymmetry. Run length features are also able to differentiate fine texture from the coarse texture. We have extracted the run length features from four directions namely, horizontal (0°), vertical (90°), left diagonal (135°) and right diagonal (45°) directions. At first, features are computed from all the four RLMs and then average value of each feature in four directions is calculated. Table 2 shows the list of various features and variable assigned to them. Table 3 presents the statistical t test results on extracted features. Significant features at 5% significant level are highlighted by bold face. As shown in Table 3, we can observe that asymmetry measure of coarseness, busyness, complexity, strength, LRE and RP are found to be relevant in distinguishing abnormal breast from normal breast and are highlighted by boldface. NGTDM extracted complexity feature is highly significant (t > 3), because information content present in the abnormal breast is more than normal breast. Complexity value is high, when there is more number of primitives in the texture. Busyness value is also high in abnormal breast than normal breast, indicating rapid changes of intensity from one pixel to its neighbours.
### Table 2  List of extracted features with variable assigned for each feature

<table>
<thead>
<tr>
<th>Features</th>
<th>Assigned variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>NGTDM $d = 1$</td>
<td>$</td>
</tr>
<tr>
<td>NGTDM $d = 2$</td>
<td>$</td>
</tr>
<tr>
<td>RLM (average values)</td>
<td>$</td>
</tr>
</tbody>
</table>

NGTDM, Neighbourhood grey tone difference matrix; CR, coarseness; CT, contrast; BS, busyness; CP, complexity; ST, strength; RLM, run length matrix; SRE, short run emphasis; LRE, long run emphasis; GLN, grey level non-uniformity; RLN, run length non-uniformity; RP, run length percentage

### Table 3  Statistical analysis of NGTDM and RLM features

<table>
<thead>
<tr>
<th>Extracted features</th>
<th>$p$</th>
<th>$t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>F1</td>
<td>0.0204</td>
<td>2.357</td>
</tr>
<tr>
<td>F2</td>
<td>0.2169</td>
<td>1.242</td>
</tr>
<tr>
<td>F3</td>
<td>0.0132</td>
<td>2.524</td>
</tr>
<tr>
<td>F4</td>
<td>0.0015</td>
<td>3.264</td>
</tr>
<tr>
<td>F5</td>
<td>0.0125</td>
<td>2.546</td>
</tr>
<tr>
<td>F6</td>
<td>0.0624</td>
<td>1.885</td>
</tr>
<tr>
<td>F7</td>
<td>0.2415</td>
<td>1.178</td>
</tr>
<tr>
<td>F8</td>
<td>0.0384</td>
<td>2.0987</td>
</tr>
<tr>
<td>F9</td>
<td>0.0119</td>
<td>2.562</td>
</tr>
<tr>
<td>F10</td>
<td>0.0103</td>
<td>2.615</td>
</tr>
<tr>
<td>F11</td>
<td>0.1297</td>
<td>-1.528</td>
</tr>
<tr>
<td>F12</td>
<td>0.0252</td>
<td>2.272</td>
</tr>
<tr>
<td>F13</td>
<td>0.3035</td>
<td>1.034</td>
</tr>
<tr>
<td>F14</td>
<td>0.1591</td>
<td>1.419</td>
</tr>
<tr>
<td>F15</td>
<td>0.0044</td>
<td>2.912</td>
</tr>
</tbody>
</table>

NGTDM, Neighbourhood grey tone difference matrix; RLM, run length matrix
We have plotted asymmetry measure of highly significant features as shown in Figure 4 (Section 4) of the revised manuscript. It is observed from the plots that asymmetry measure of features namely, coarseness (F1), Busyness (F3), Complexity (F4), Strength (F5) of NGTDM for 3 x 3 neighbourhood, Complexity (F9), and Strength (F10) of NGTDM for 5 x 5 neighbourhood and RLM extracted F12 (LRE) and F15 (RP) are high for most of the abnormal samples in comparison with the normal samples. Asymmetry between right and left breast will be more in abnormal thermograms in comparison with the normal thermograms is due to the presence of tumour and local vascularisation. Hence, these are the important features, can be used for differentiating normal and abnormal breasts in early detection of breast cancer.

Figure 4  Plot of asymmetry measure of feature values (significant) for normal and abnormal breasts (see online version for colours)

SVM and ANN classifiers are trained and tested using significant features. Average classifier performance of each classifier is calculated using K-fold cross validation (K = 10) in order to reduce the bias in selecting the samples. Performance of SVM is
compared using various kernels namely, quadratic, polynomial and Gaussian. SVM with quadratic kernel performed better in comparison with other kernel functions. Back propagation ANN with three hidden layers are used for classification. Table 4 presents the best results obtained by SVM quadratic and ANN classifiers. From Table 4, it is observed that ANN classifier performed better in comparison with SVM classifier. We have obtained an average accuracy of 80%, sensitivity of 94% and specificity of 71.4% using ANN classifier. It is also observed that sensitivity is high in both the classifiers.

### Table 4 Classifier performance using SVM and ANN

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Accuracy (%)</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM quadratic</td>
<td>76</td>
<td>82.85</td>
<td>72.3</td>
</tr>
<tr>
<td>ANN</td>
<td>80</td>
<td>94</td>
<td>71.4</td>
</tr>
</tbody>
</table>

ANN, artificial neural network

Computationally efficient and relevant features are very essential in the development of CAD for breast thermography. The proposed method extracted features from computationally less expensive NGTDM, since NGTDM uses column matrix. Computation time for NGTDM is less in comparison with the grey level cooccurrence method (Acharya et al., 2012; Krawczyk and Schaefer, 2014; Milosevic et al., 2014; Schaefera et al., 2009). The size of the data used in this article is small. If more samples are made available with different types of cancer cases, then detailed analysis can be made using the proposed method.

### 5 Conclusion

Extraction and selection of appropriate features from breast thermograms are very important to improve the accuracy of detection of breast cancer. Proposed method extracted various NGTDM and RLM based features from automatically segmented breast thermograms. Features are found to be significant in classifying normal and abnormal breasts using statistical test. Complexity and run percentage features are highly significant in distinguishing abnormal breasts from normal breasts. Extracted features are computationally less expensive and attained an average accuracy of 80%, sensitivity of 94% and specificity of 71.4% using back propagation neural network classifier.

### References


Texture analysis of breast thermograms


