Detection of Breast Abnormality Using Rotational Thermography

Sheeja V. Francis, M. Sasikala and Sandeep D. Jaipurkar

Abstract Breast cancer is considered to be one of the major causes for high mortality rates in young women in the developing countries. Survival rate in breast cancer patients may be improved significantly by early detection. In order to detect cancer in its initial stages breast screening is recommended for women over 40 years of age. Due to the limitations of existing breast cancer screening techniques alternative modalities such as thermography are being explored. An elevation in local surface temperature due to an underlying pathology is considered as one of the earliest indications of an underlying cancer. Such regions are represented as hotspots on a conventional thermogram. Detection of these hotspots from conventional breast thermograms is quite challenging, mainly due to incomplete image acquisition. A novel technique called rotational thermography has been developed to address this issue. In this chapter, a frame work has been presented for developing a breast cancer screening system using thermograms acquired with this new imaging modality. Image features are extracted from rotational thermograms in spatial, bispectral, and multi-resolution domains. Optimal features are identified using genetic algorithm and automatic classification is performed using support vector machine. In addition to screening, attempt has been made to characterize a detected abnormality as benign or malignant. As rotational thermography acquires images of the breast in multiple views, study is carried out to locate the position of the tumor in correlation with ultrasound and biopsy findings. Thus the potential of the system for screening, characterization, and localization of breast abnormalities is explored.

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1 Introduction

Breast cancer is reported to be the most predominant of all cancers detected in women. Cancer facts and figures released by the American Cancer Society estimates that about 29% of all reported cancers in 2015 would be of the breast [1]. It is estimated that one in every eight women possesses the risk of developing breast cancer in their lifetime. The estimated mortality rates are also very high, with breast cancer contributing to 15% of all cancer deaths.

The mortality rate due to breast cancer is found to be rising in both the developed and the developing countries. These rates may be brought under control if the disease is detected early, leading to effective treatment and prognosis. As early detection can lead to better survival chances, women above 40 years of age are advised to undergo screening for breast cancer annually. Currently, mammography is used as the gold standard imaging technique for the purpose. However, the diagnostic ability of this technique is found to be compromised in women with dense breasts. Keyserlingk et al. [2] have reported that mammography fails to detect small tumors of size less than 1.66 cm on an average and hence is not able to detect cancer at an early stage. Further, patients who undergo mammographic procedure are at the risk of radiation hazards due to repeated X-ray exposures. Hence, continuous efforts are being made to develop radiation safe imaging techniques for the early detection of breast cancer. According to Gautherie et al. [3], thermography is one such technique that can detect breast cancer 8–10 years ahead of mammography. Although thermography is popularly used for mass screening of fever [4], several studies have reported on its early detection capability of breast cancer in the last two decades [5–8]. Understanding of the thermal profile of human breast is quite essential to evolve thermography for breast cancer detection.

1.1 Thermal Profile of Human Breast

The core temperature of human body is reported to be around 37 °C when the ambient temperature is maintained at 25 °C. The transfer of heat from core of the body to skin surface is a complex thermo-biological process. When subjected to extreme environmental temperatures, the vaso-regulatory system of our body helps to maintain the thermal equilibrium by triggering shivering or sweating as reflex mechanisms. The optimal temperature range in which a slightly dressed human body can maintain thermal equilibrium is 20–25 °C. Hence, thermographic studies are conducted in controlled environments maintained within this temperature range. The mean temperature of human breasts is found to vary from person to person based on several factors such as environmental conditions, physical exertion, menstrual cycle, anxiety, etc. Also, different regions within the breast exhibit different temperatures. The average temperature of breast surface is reported to be around 30 °C in a controlled environment at 20 °C [9]. Several researchers have established that the surface temperature of a cancerous region is significantly higher than that of the surrounding normal regions. Hence, an abnormal breast condition may be detected by analyzing the temperature differences within a breast region. Further, a temperature difference of more than 0.5 °C between right and left breasts is reported to be indicative of abnormality [10]. Hence, exploring the thermal asymmetry between the contra-lateral breasts is widely practiced for breast cancer detection. Due to advancements in sensor technology, infrared cameras with enhanced thermal resolution of less than 0.1 °C are available. These are capable of sensing the subtle temperature variations and are used for evaluating breast conditions in breast thermography.

2 Breast Thermography

The first instance of using infrared imaging for cancer diagnostics can be traced to 1956, when it was discovered that surface temperature over cancerous tissues in a breast was higher than the surrounding normal regions [11]. The high rate of metabolic activity around cancerous tumors triggers a huge demand for supply of nutrients. Consequently, an increased blood flow is ensured in order to nourish these cancer cells by recruiting dormant vessels and creating new ones (neo-angiogenesis). This process leads to vascular asymmetry and increase in regional surface temperatures in the breasts, which may be considered as the earliest signs of breast cancer [12, 13]. Breast thermography involves capturing these variations and interpreting them for early detection of breast cancer or for monitoring its prognosis.

A large-scale study popularly known as breast cancer detection and demonstration project (BCDDP) was conducted in the United States in the early 70s to evaluate the diagnostic ability of breast thermography. According to the report of the working group, the diagnostic value of infrared imaging was considered to be poor [14]. This was followed by a period of uncertainty and waning interest in the procedure. However, poor study design, use of untrained technicians, improper environmental controls, and protocols led to the failure of the project [15].

Since mid-70s, significant improvements have been made in infrared technology, sensor arrays, and computing systems for military purposes. This has renewed the research interest in breast cancer detection through thermography. State-of-the-art breast thermography uses highly sensitive infrared cameras and software systems to represent thermal variations of the breast surface in the form of high-resolution images called breast thermograms. The procedure is noninvasive, comfortable, and radiation safe. An abnormal breast thermogram has been reported to be an important high-risk marker for cancers that might develop in the future [16].

Both passive and active methods are being practiced in breast thermography. In passive thermography, the regions of interest are naturally at a higher or lower temperature than the background. Hence, the infrared rays emitted from these regions are picked up effectively by the camera system. An active approach is necessary when such regions are usually in equilibrium with the surroundings. Thus in active thermography, an energy source is used to produce a thermal contrast between the regions of interest and the background by applying a cold challenge. It is usually implemented as a blow of hot air or chemical vaporization on the skin surface. Though Amalu [17] has reported that application of cold challenge does not lead to performance improvement in active breast thermography-based systems, continuous research has been going on in this area.

Though thermography is a promising screening tool for breast cancer, diagnosis is usually done manually by skilled professionals. Hence, interpretations made from thermograms are highly subjective in nature. In order to overcome factors such as shortage of trained personnel and operator variability, a computer-aided diagnostic (CAD) system needs to be developed. The advancements made in thermal imaging systems and pattern analysis techniques may be used to build a reliable system for breast cancer detection based on thermography. Such a system can be used for breast cancer screening in developing countries, especially by primary health care professionals in rural areas where specialized health care is lacking. Several researchers have worked on developing CAD systems for breast cancer detection using thermograms acquired by conventional breast thermography technique.

2.1 Conventional Breast Thermography

In the conventional technique for breast thermography the patient is seated in front of the infrared camera at a distance of 80–100 cm. This distance is chosen so as to image the complete torso of the subject with good resolution at the field of view of the camera. The schematic representation of conventional breast thermography

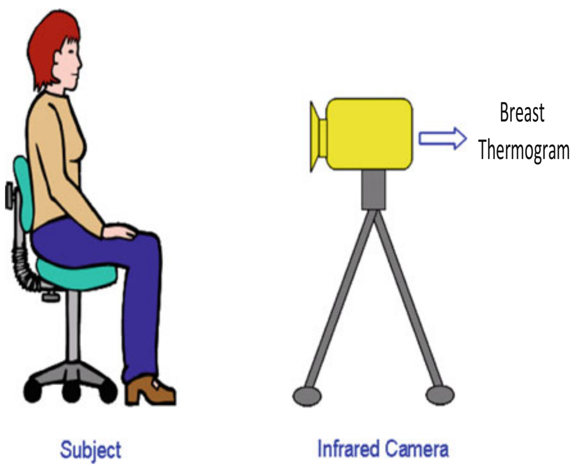

Fig. 1 Schematic representation of conventional breast thermography technique

technique is shown in Fig. 1. In this method infrared images of the breast are acquired in three views, viz., Contra-lateral, Medio-Lateral Oblique, and Axillary.

Most of the CAD systems presented in literature use contra-lateral or frontal thermograms and are confronted with two problems. First, tumors in the inferior regions of the breast are obscured behind the natural sag and often go undetected. Second, the neck carotid and infra mammary folds are visible in the images. These are normally hot regions that may lead to wrong diagnosis if not removed. Segmentation of the breasts from these areas is a pre-requisite for effective CAD systems and is quite a challenge till date. The image acquisition and interpretation processes are operator dependent and are found to vary across patients. In order to address these issues a new thermal imaging technique called rotational thermography has been evolved.

2.2 Rotational Breast Thermography

A novel setup known as the Mammary Rotational Infrared Thermogram (MAMRIT) unit [18] is used for acquiring rotational breast thermograms. The unit comprises an imaging chamber with a patient table on its top as shown in Fig. 2. The ambient temperature and humidity inside the chamber are controlled with an inbuilt air conditioner.

The subject lies in prone position on the patient table of the MAMRIT unit with one breast suspended through the small circular aperture into the imaging chamber beneath. An infrared camera is fixed at the free end of a robotic arm situated inside the MAMRIT chamber. The arm is programmed to revolve around the suspended breast in angular steps of 30°. The infrared camera captures images of breast at every step. Thus 12 views of the breast are obtained in one rotation ensuring complete imaging of the breast. Surface temperature information of the entire breast is captured and may be displayed by placing the cursor at required spatial positions. The acquisition of temperature information is repeated after lowering the ambient temperature to understand the tissue response to external stimuli. All the images are stored along with patient information, the camera position, ambient temperature, and time of acquisition. The set of thermograms obtained before and after lowering of ambient temperature are called precool and post-cool series, respectively. The same procedure is repeated for the other breast.

The images are acquired with patient consent and Institutional review board—approved protocol, using infrared camera ICI7320P [19]. The camera is an uncooled bolometer type with spatial resolution 480×640 pixels. The inbuilt software represents the raw temperature data picked up by the detector in the form of pseudo-color images. The 'hot' color palette is used which varies from blue to red in increasing order of temperature (heat). A temperature variation of around 10 °C is observed in the human breast. These variations are represented on thermogram images by grouping pixels into 10–12 bands, such that the temperature

Fig. 2 Views of MAMRIT Unit

variation between successive bands is around 1 °C. The minimum temperature resolution is 0.01 °C. At such resolution, the slight variations in intensity present within the bands are not perceived by the human eye. Nevertheless, these pixel intensities may be observed by placing the cursor on regions of interest and more so by computer vision techniques. A specific pattern of temperature variation is observed along the vertical direction in rotational breast thermograms of normal subjects. The nipple region is found to be the coldest and the temperature increases in regions closer to the chest wall. This pattern is found to extend across the breast when all twelve views are observed. In case of abnormality, bands that represent higher temperatures are found protruding into the zones of lower temperature thereby disturbing the characteristic temperature pattern. Figure 3 shows the complete sequence of precool rotational images of single breast (Left side) at angles 0°, 30°, 60°, 90°, 120°, 150°, 180°, 210°, 240°, 270°, 300°, and 330°, respectively.

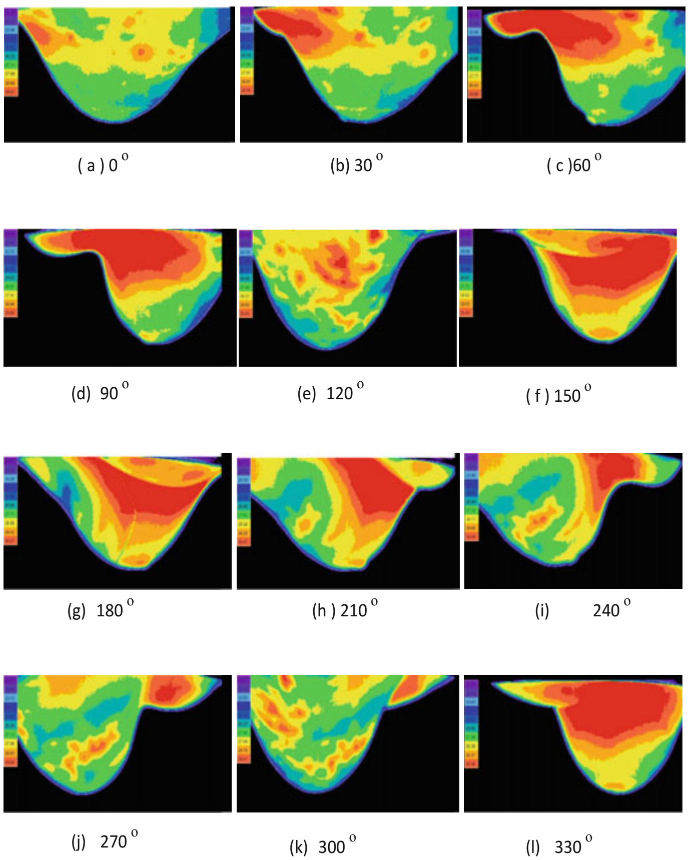

Fig. 3 Image sequence acquired by rotational breast thermography

The rotational breast thermography technique contains more diagnostic information than the conventional technique due to the following reasons.

- Chances of missing a tumor are much less as the breast is imaged completely.
- As images are captured by moving the camera around the suspended breast, all tumors that are located within 4.5 cm from breast surface are detected (at least in a few closest views), whereas, in the conventional method, the heat emissions from such depths are scattered and lost in the overlying tissues.
- Cold challenge may be easily implemented as the breast is imaged in a temperature-controlled chamber.
- Movement artifacts are greatly reduced as the patient is made to lie comfortably in prone posture during image acquisition.

2.3 Outline of the Chapter

The study is presented in two sections. In the first, a screening system is developed for detecting breast abnormality in rotational thermograms by exploring texture features in various domains. Optimal features are identified using genetic algorithm in order to design a reliable system for detection of breast abnormalities. Automatic classification of normal, benign, and malignant conditions is carried out to study the ability of rotational thermography-based system in characterizing the detected abnormality. The capability of the system to locate the abnormal region has been studied in correlation with ultrasound findings in the second section.

3 Screening and Characterization of Breast Abnormality in Rotational Thermograms

During the last two decades several computer-aided systems have been developed for screening of abnormality from conventional breast thermograms. Such systems include general image processing techniques such as segmentation, feature extraction, and classification. Several segmentation methods have been proposed to extract whole breasts and specific regions of interest as well [20–26]. Spatial-domain statistical features [27–31], wavelet-based features [32, 33], higher order spectral features [34], bispectral invariant features [35], and fractal dimension [36] have been employed for classifying breast thermograms. Numerical modeling of thermal properties of breast has been used to aid interpretation from breast thermograms [37–39]. The relationship between texture features and surface temperature changes has been well established in literature [40]. Hence, texture features are extracted from regions of elevated temperatures in rotational thermograms for breast screening. As a preliminary study failed to prove the effectiveness of existing cold challenge mechanism, only rotational thermograms of precool series were used for the study.

Various breast abnormalities exhibit distinct temperature profiles and may be broadly characterized as benign or malignant. According to Jayashree et al. [9], the local temperature rise is less than 1 °C in benign regions while it is more than 1.5 °C in case of malignancy. This margin between benign and malignant conditions may be even less when malignancy is in its initial stages. Further, the patterns of thermal variations between normal and benign conditions are often indistinguishable. Hence, the characterization study is also important for detection of breast cancer. Examples of normal, benign, and malignant thermograms are shown in Fig. 4.

From the observations made from literature survey on conventional thermography-based systems and preliminary study on rotational thermography, a CAD system has been developed for screening and characterization of abnormality in rotational breast thermograms. The general block diagram of this system is shown in Fig. 5.

Breast cancer detection potential of rotational thermography is evaluated by extracting texture features from rotational breast thermograms in various domains, analyzing and classifying normal and abnormal breast conditions. The potential of these features in characterizing a detected abnormality as benign or malignant has also been studied. Principal component analysis (PCA) and genetic algorithm (GA) are used to identify the most discriminative features for improving the screening and characterization accuracy of the system.

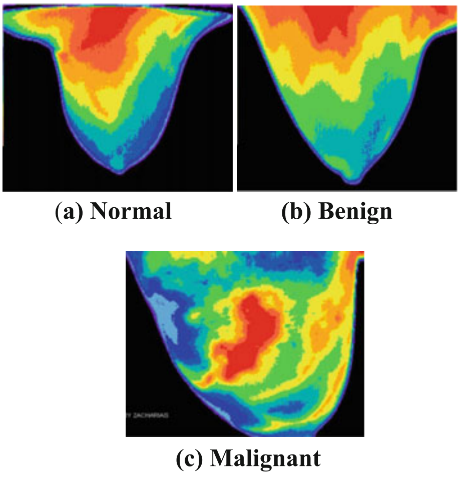

Fig. 4 Samples of rotational breast thermograms

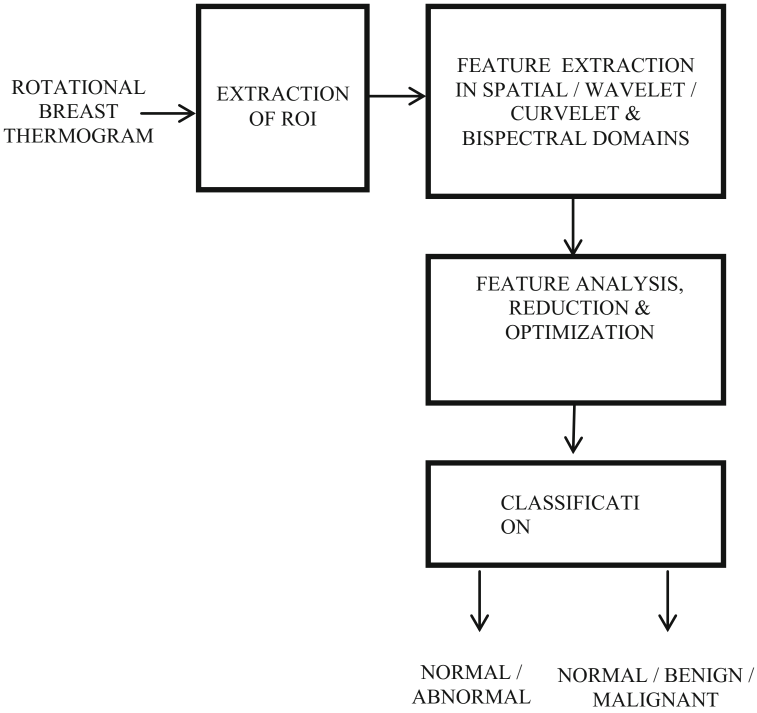

Fig. 5 Rotational breast thermography-based system for screening and characterization of abnormality

3.1 Preprocessing—Segmentation

As the first step, the regions of interest are extracted from rotational thermograms. Normal and abnormal breast thermograms are converted into gray scale as shown in Fig. 6. It is observed that the temperature variation in a normal breast follows a specific pattern in the vertical direction as discussed earlier: an increase in temperature from the nipple to the chest wall. The camera captures the images of breast at every angular increment of 30° by rotating around it, resulting in a series of 12 thermograms. Given the average size of breast, each successive view (image) in the series includes a region already covered in the previous one. Thus, there is partial overlap of regions in successive thermograms in a series.

The distance between the breast and camera is adjusted to obtain complete view of the breast within the frame. According to clinician's requirement, 30% of the total breast area is extracted at the center of image to form the ROI. This extraction is done on all 12 thermograms in a series to ensure that the entire breast area is examined.

Fig. 6 Rotational breast thermograms in gray scale

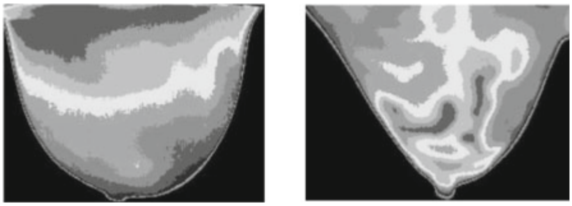

Fig. 7 Regions of interest extracted from rotational breast thermograms

(a) Normal **(b) Abnormal**

ROI is extracted using the following steps.

- Obtain the whole breast region from thermogram and calculate its area.
- Identify a vertical axis, midway between the right and left extremes of the breast with nipple position as lower most reference.
- Extract a symmetrical rectangular region about the central axis as the ROI when its area becomes equal to 0.3 $\times$ total area of breast.

The central 30% of breast area is extracted from all 12 views in a series of thermograms to form regions of interest. As the entire breast area is covered by this process, no information is lost. The ROIs thus obtained from normal and abnormal thermograms in Fig. 6 are shown in Fig. 7.

3.2 Feature Extraction

Statistical features that best represent the thermal variations in thermograms are extracted as features. First- and second-order statistical features are obtained from the regions of interest of normal and abnormal thermograms. First, these features have been extracted and analyzed in the spatial domain, followed by multi-resolution domains such as wavelet and curvelet.

- **First-Order Statistical features**

First-order statistical features, viz., mean, variance, skewness, and kurtosis, represent the spatial distribution of gray-level intensities in a given ROI. These simple histogram-based statistical features extract global texture information from the thermograms [41]. Mean represents the average intensity of pixels in the ROI and does not carry significant information. Variance feature represents the deviation of pixel intensities from the mean value of the ROI. Skewness and Kurtosis represent the third- and fourth-order deviations from the mean. Since abnormal regions contain large variations in intensity, features such as variance, skewness, and kurtosis contain significant information.

- **Second-Order Statistical Features**

Second-order statistical features also known as texture features are extracted from normalized gray-level co-occurrence matrices (GLCMs) constructed from the ROIs. Thirteen texture features described by Haralick et al. [42] have been computed. These include angular second moment (ASM), contrast, correlation, sum of squares, inverse difference moment, sum average, sum variance, sum entropy, entropy, difference variance, difference entropy, information measure of correlation 1, and information measure of correlation 2. The ASM feature represents the extent of uniformity in textures. Contrast represents the amount of local intensity variations in an image. Correlation measures linear dependencies in the image. Inverse difference moment is a measure of local homogeneity while entropy measures the range of randomness of the gray-level distribution in the image. All the features derived from normalized co-occurrence matrices contain information about the texture of an image. However, it is difficult to identify the specific texture characteristics represented by each of them.

3.2.1 Wavelet Transform

Wavelet transform is used in signal analysis to overcome the time–frequency localization limitations of Fourier transform. A wavelet is a waveform that exists for a limited duration and has a zero average value. A mother wavelet is a small wave of distinct signature. Wavelet analysis convolves shifted and scaled mother wavelets with the input signal. In two-dimensional signals (images), wavelet decomposition is performed with separable filtering along the rows and columns. At the first scale of decomposition, the image is represented by four sub-bands (three directional sub-bands and 1 approximate band). The wavelet coefficients in these sub-bands carry information about intensity variations in horizontal, vertical, and diagonal directions in the image. Thus wavelet analysis is considered as an image decomposition method that offers good space–frequency localization. Statistical features extracted from the wavelet sub-bands may be used to analyze the underlying characteristics of an image. Figure 8 illustrates image decomposition using wavelet transforms at levels (scales) 1 and 2.

Transformed domain features pose problems of high dimensionality and redundancy due to decomposition into multiple sub-bands. A sub-band is identified for each ROI based on maximum variance criterion. Statistical features are extracted from this sub-band, instead of using the coefficient values directly thereby leading to dimensionality reduction of the feature set. As Symlet mother wavelet is

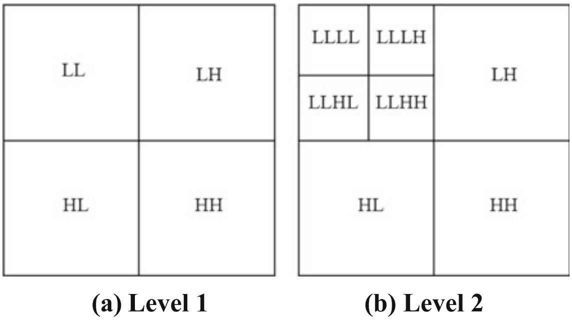

Fig. 8 Representation of 2D wavelet decomposition

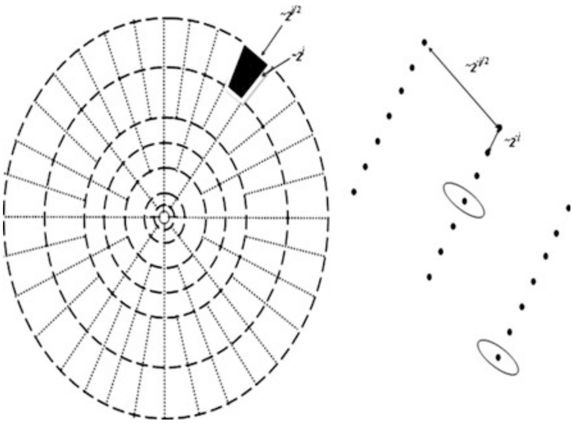

Fig. 9 Continuous curvelet transform decomposition in frequency domain

most suited to detect a deviation from symmetry, it is used to decompose the ROI at level 2. The sub-band with maximum variance was selected for extracting features at decomposition level 2.

3.2.2 Curvelet Transform

Curvelet transform developed by Candes and Donoho is a multi-resolution tool that includes directional aspect while decomposing an image in addition to the scale and position features of a wavelet transform [43]. Most biomedical images contain curvilinear structures. Curvelet transform at a predefined scale and orientation decomposes an image into smaller blocks so as to approximate curves as piecewise linear structures. Curvelet transform resolves the frequency domain into multidirectional and multiscale fan-shaped wedges as shown in Fig. 9. The scale becomes smaller from outside to inside and the number of directions gets reduced by a factor of two after an interval of one scale.

Candes et al. [44] proposed two distinct implementations of discrete curvelet transform: one using unequispaced fast Fourier transform (USFFT) and the other using a wrapping method. The more common of them, the fast discrete curvelet transform (FDCT), implemented by the wrapping technique has been used in this work.

In curvelet domain, the ROI is decomposed at scale 2 and orientation 8. The sub-bands of curvelet decomposition comprise of curvelet coefficients. The directional sub-band with maximum variance was selected for extracting features. The extracted features are analyzed statistically using student's t test to study their discriminating ability and are classified using SVM classifier. The performance of the classifier is validated using the leave-one-out method.

3.2.3 Extraction of Bispectral Invariant Features

The potential of higher order spectral features (HOS) has been investigated with great interest in the analysis of medical signals such as EEG. The bispectrum of a random signal $x[k]$ is defined as the third-order spectral feature in the frequency domain as given in Eq. 1:

$$B(f_1,f_2) = X(f_1)X(f_2)X^*(f_1+f_2), \tag{1}$$

where$X$ (f) is the Fourier transform of $x[k]$ and f *is* the normalized frequency (between 0 and 1).

The bispectrum of a real-valued discrete-time signal exhibits symmetry properties. Hence, computation may be done over a triangular region in bi-frequency space as shown in Fig. 10.

The integral of bispectrum along a straight line of slope, 'a', gives a complex quantity, containing magnitude and phase information as shown in Eq. 2. This phase component is called the bispectral invariant feature ($\emptyset(a)$) as defined by Eq. 3:

$$I(a) = \int_{f_1=0^+}^{\frac{1}{1+a}} B(f_1, af_1)\mathrm{d}f_1 = I_{\mathrm{Re}}(a) + jI_{\mathrm{Im}}(a) \tag{2}$$

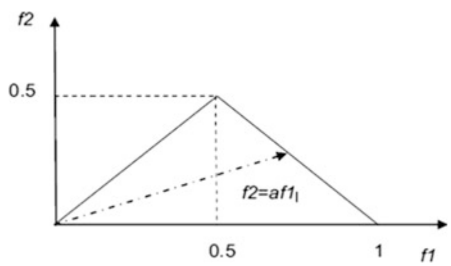

Fig. 10 Region of bispectrum computation in the bi-frequency space

$$\emptyset(a) = \arctan\left(\frac{I_{\mathrm{Im}}(a)}{I_{\mathrm{Re}}(a)}\right). \quad (3)$$

These features have been shown to be invariant to translation, scaling, and amplification [45]. Being sensitive to shape changes in input patterns, these may be used to detect deviations from normal patterns in thermograms. Signal processing principles have been extended to 2D (images) in order to extract bispectral invariant features from thermograms. The input image is first converted into a set of 1D projections using Radon transform at several angles. Bispectral invariant features are computed from each of these projections. In this work Radon transform has been computed at six angles with four slopes each. Thus each ROI is represented by a set of 24 bispectral invariant features.

3.3 Feature Analysis

Features extracted from normal and abnormal ROIs in various domains are analyzed and classified using SVM classifier. Average value of each feature is computed for both classes in all the domains. Features extracted in spatial domain and transformed domains are analyzed statistically using student's t test at 95% confidence level. The null hypothesis is framed such that the features extracted from normal and abnormal groups belong to the same class. If the p value returned by the test is found to be less than 0.05, this null hypothesis is rejected. Thus features with $p < 0.05$ are found to be statistically significant than the others and can discriminate an abnormal ROI from a normal one more effectively.

Feature analysis by student's t test proved that the first-order statistical features were statistically insignificant in almost all domains. It is also observed that among the 13 texture features, 8 were found to be significant in spatial domain, 4 in wavelet, and 9 in curvelet domains. The level of statistical significance was found to be highest with the curvelet features. Among the bispectral invariant features, those extracted from all angles were found to be statistically significant except at angle 0. This phenomenon may be explained from basic principles as given. The Radon transform at 0° produces the 1D projection of intensity variations along the horizontal direction at the center of the ROI. It may be observed that pattern changes on a thermogram are minimal in this direction, compared to the vertical and other (radial) angles. Finding the optimal number of angles and slopes for bispectrum computation is found to be a major issue in this domain. Statistical analysis reveals that among the features extracted, the curvelet transform-based co-occurrence features are more suited for the problem.

As the first-order statistical features were found to be statistically insignificant, these were eliminated from further investigation. A two-stage classification scheme has been implemented using texture and bispectral features. In the first stage, the screening ability of the system has been tested in all domains followed by the evaluation of characterization ability.

3.4 Classification

The Support Vector Machine (SVM) classifier is used for automatic detection of abnormal conditions in thermograms. SVM is a supervised learning algorithm that finds wide application in pattern recognition problems. It generates a robust mapping function from a set of training data [46]. SVM is of great use in classification problems where the input data is not linearly separable. In such cases, nonlinear kernel functions may be used to transform the input data to a higher dimensional feature space where the separability is better. The order of these functions may be varied iteratively until the distance between the decision surface and nearest sample is maximized. Thus SVM constructs N-dimensional hyper-plane for optimal separation of input data into classes [47].

In this work a binary SVM using polynomial kernel of order 3 has been used for the classification purpose. Performance of the classifier is validated using leave-one-out method. In this method, a single observation from the original sample is used as the test data, while the remaining observations form the training set. The validation scheme is complete when each observation in the sample has been used as the test data at least once. The performance of the classifier has been evaluated by finding accuracy, sensitivity, and specificity measures from confusion matrices. Traditionally, the classification results of a test under study are compared against those of a standard test. The observations made in four categories, viz., true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), are presented in a (2×2) matrix. Accuracy is the measure of true results (both true positive and true negative) obtained by the test in the entire population. Sensitivity represents the probability that a test will produce a positive result when used on diseased population. Specificity gives the probability that a test will produce a negative result when conducted on normal population.

3.4.1 Feature Reduction Using Principal Component Analysis

Principal component analysis is a statistical procedure used to convert a set of highly correlated input variables into a smaller set of uncorrelated variables popularly called as principal components [48]. This orthogonal transformation results in a reduced set of variables as the number of principal components obtained is usually less than the number of original inputs. These components are formed by linear combinations of all input features and are arranged in decreasing order of their variance. The composition of these principal components may be analyzed by observing their respective Eigen vectors. PCA is generally used as a feature reduction technique in classification problems when the input feature set is large and redundant.

3.4.2 Selection of Optimal Features Using Genetic Algorithm

Although PCA gives a reduced feature set, all features have to be extracted in the first place in order to form the principal components. PCA provides fewer discriminative inputs that reduce classifier complexity but fails to be of any aid in the exhaustive feature extraction process. Hence, an effective search algorithm may be employed to select the most discriminative subset of features. Genetic algorithm (GA) is used to identify the optimal features that can lead to best classification accuracy. GA is a search algorithm that models the natural process of biological evolution using operators such as selection, mutation, and crossover to find the optimal solution for the specific problem [49].

In GA, each feature set is represented as a chromosome. A chromosome is represented in form of a binary string of length equal to the number of features. A fitness function, usually a maximizing or minimizing function, is defined for the problem. The fitness value of each chromosome is computed. The selection of a chromosome is based on the ranking of its fitness value. The GA-based approach begins with creation of an initial random population and its evaluation using the fitness function based on the classifier error. The chromosomes in the population are ranked according to their fitness values. A few with highest fitness values (Elite) are directly transferred to the next generation. Using selection methods such as roulette wheel, tournament, etc., chromosome pairs are selected to undergo cross over and mutation to form new population. The process is repeated iteratively until the GA converges and the best chromosome is returned. The composition of the best chromosome may be examined to identify the optimal features.

3.5 Results of Classification

The SVM is trained and tested with a set of feature vectors extracted from normal and abnormal thermograms by the leave-one-out method first for screening and then for characterizing an abnormality as benign or malignant.

- **Screening of Abnormality**

The training set consisted of 36 normal and 36 abnormal thermograms (18 malignant and 18 benign). Classifier performance for screening of breast abnormality when features of various domains were used is presented in Fig. 11. It is observed that the screening performance of the system is at its best, when curvelet-based texture features are used, followed by bispectral invariant features. The system is able to detect an abnormal thermogram with a high accuracy of 94.4% in curvelet domain with sensitivity and specificity of 97.2 and 91.7%, respectively. In an earlier study, conventional thermography-based system had resulted in an accuracy of 90.91% when curvelet texture features were employed [50].

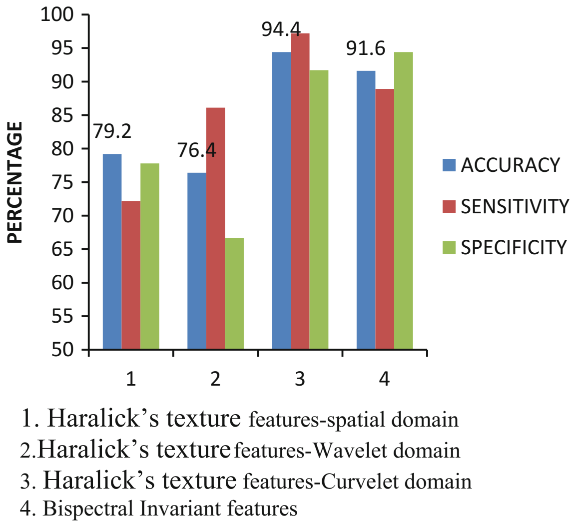

Fig. 11 Classifier performance for screening of breast abnormality in rotational breast thermograms

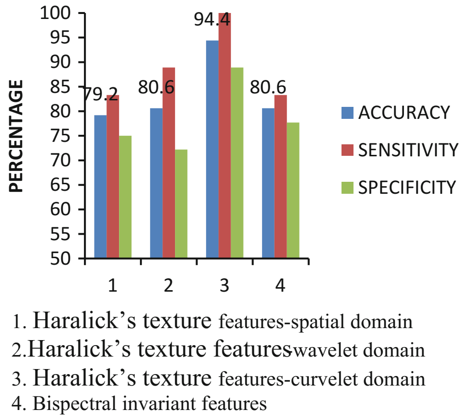

Fig. 12 Classifier performance for characterization of breast abnormality in rotational thermograms

- **Characterization of Abnormality**

Features extracted from 36 rotational thermograms in each class have been used for classifying test inputs into benign-malignant, normal–malignant, and normal–benign classes using features extracted in all domains. Classifier performance for characterization of breast abnormality as benign/malignant is presented in Fig. 12. It is observed that the performance of the system for characterizing a detected abnormality as benign or malignant is also at its best when curvelet-based Haralick's texture features are used. An abnormal condition could be characterized as malignant or benign with an accuracy of 94.4% in the curvelet domain.

The results of binary classifications using curvelet-based texture features are shown in Fig. 13. It is observed that a malignant condition could be detected from

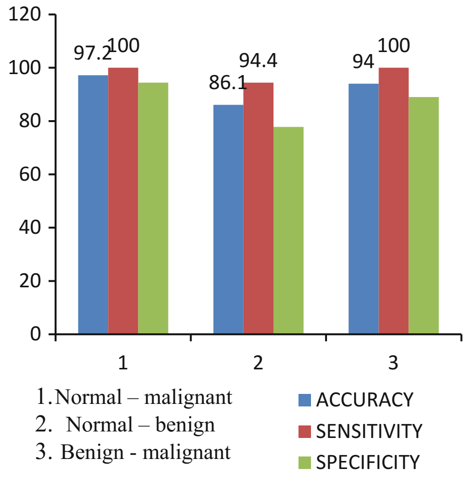

Fig. 13 Performance of SVM classifier using curvelet-based texture features for normal/malignant, normal/benign and benign/malignant classifications

Table 1 Classifier performance for screening and characterization of breast abnormality in rotational thermograms using optimal features selected by GA

Features	Classes	Accuracy (%)	Sensitivity (%)	Specificity (%)
Optimal curvelet transform-based texture features	Normal–abnormal (screening)	94.4	97.2	91.7
	Normal–malignant	98.6	100	97.2
	Normal–benign	88.9	94.4	83.3
	Benign–malignant	95.8	100	91.7

other classes with 100% sensitivity. As the tissue temperature in a malignant region is significantly higher than benign and normal conditions, the classifier is able to detect all malignant cases in the set of input images.

- **Classification using PCA- and GA-Based Feature Selection**

When PCA was used for feature reduction, it was observed that the first 3 principal components (formed from the 13 curvelet-based texture features) could produce an uncompromised classifier performance. As each component is a linear combination of all feature inputs, those which offered maximum contribution were identified from their Eigen vectors. It was found that features such as difference variance, sum of squares: variance, contrast, sum variance, and sum average had contributed significantly to the first principal component.

Incidentally, GA also identified three of these as optimal texture features: contrast, sum of squares—variance and difference variance. On correlating with the results of PCA, it is observed that these features had offered maximum contribution to the first principal component. These were also found to be statistically significant with least p values. Nevertheless, a global optimization technique such as GA has validated the significance of these features. These features represent variations in the distribution of intensity values in thermograms, most effectively and may be considered to carry significant thermal signatures of abnormality. The results of classification with optimal features are presented in Table 1.

A significant improvement is observed in the classifier performance for characterization of abnormality with the use of optimal features. Although an improvement in classifier performance is observed with the use of optimal features, the accuracy of detecting benign abnormality from normal conditions is only 88.9%. This is observed to be lower than the accuracy in malignant–benign classes. On analyzing the sample thermograms used, the temperature difference between normal and benign conditions was found to be 0.7 ± 0.3 °C and that between malignant and benign conditions was found to be 1.7 ± 0.7 °C. As the margin of temperature difference between the benign–normal classes is lower, it is difficult to detect a benign condition from a normal condition in thermograms, resulting in lower accuracy in this class.

4 Localization Study Using Rotational Thermogram Series

As discussed earlier, images are acquired at spatial increments of 30° resulting in a series of 12 thermograms. Given the size of breast, there is partial overlap of regions in successive thermograms of a series. To ensure that the entire breast is examined, 30% of the total area is extracted as ROI from the center of the breast in each view. However, it is found that these ROIs cannot be identified uniquely with the respective breast views due to the overlaps with ROIs of succeeding and preceding views. Nevertheless, there is a non-overlapped central region in each ROI.

- If an abnormality is represented as hot spots in a confined small area, it will be detected in this central portion of one of the views. Thus, the accuracy of locating it is better.
- If an abnormality is observed at the periphery of breast at one view, it will be seen in the central portion of breast in one or two successive images down the series.
- If an abnormality is represented as a larger hot area, it will be seen in the central portion of more than one view. In such cases, the accuracy of locating it will be erroneous.

As curvelet-based texture features were found to perform best for classification purpose, these were extracted from the ROIs. These feature vectors are given as test inputs to SVM classifier in order to detect abnormal views. The classifier is trained with curvelet texture features extracted from 36 thermograms each in normal and malignant groups. The spatial views where an abnormality was detected by the system are noted for further analysis. Finally, optimal features selected by GA have also been used for improving the localization ability.

4.1 Results of the Localization Study

The study includes precool series—thermograms of 36 malignant patients (12 thermograms per patient). A report indicating hyper-thermal views, as interpreted by the thermographer, is made available for each subject. According to this report, several views are indicated to be hyper-thermal. After scrutiny by radiologist, 2–5 (views) thermograms were identified as abnormal for each patient. The details of thermograms used in the work are given in Table 2.

Table 2 establishes that the distribution of heat on the breast surface is based on the severity of the underlying tumor. It may be observed that hot regions are confined to only 2 views in 10 cases, while in others, 3–5 views may be involved. Thirty-six malignant cases with 12 thermograms each (a total of 432 thermograms, wherein 108 were abnormal) are used for locating the abnormality. For an abnormal patient, when all 12 images in a series were tested with a trained classifier, only thermograms acquired at certain views were detected as abnormal.

Results of the localization study are analyzed by evaluating the performance of the system from confusion matrices. It was observed that all (108) abnormal views were detected by the system when curvelet-based texture features were employed. Out of 324 normal thermograms, 288 were identified correctly by the system, resulting in an accuracy of 91.6%, sensitivity of 100%, and specificity of 88.9%. Improved performance was obtained when optimal features were used for classification as shown in Table 3.

The optimal curvelet texture feature-based system resulted in an accuracy of 93.5% with sensitivity and specificity of 100 and 90.7%, respectively. It is found that all the identified abnormal views were detected, while 30 normal views were misclassified as abnormal. Hence, detailed case studies were conducted to validate the performance of the system with the opinion of expert radiologist. The abnormal views detected by the system were compared with expert opinion and respective ultrasound findings.

Table 2 Details of thermograms used in the localization study

No. of malignant patients (36)	No. of abnormal views/patient	No. of abnormal views
10	2	20
20	3	60
2	4	8
4	5	20
Total no of abnormal views		108

Table 3 Confusion matrix for localization of abnormality using optimal curvelet-based texture features

		Detected class	
		Normal	Abnormal
True class	Normal (324)	(TN) 294	(FP) 30
	Abnormal (108)	(FN) 0	(TP) 108

All regions which were detected as abnormal by the proposed system, expert's interpretation, and ultrasound as well were found to be malignant, resulting in 100% sensitivity. This was verified with biopsy results in each case. It is found that a normal breast region with increased vasculature is reported to be hyper-thermal on a thermogram, but normal on ultrasound. Such cases result in false positives and reduce the accuracy and specificity of the system when used as a standalone unit.

From results of the localization study, it is found that the views where a thermogram was detected as abnormal could always be mapped to the abnormal quadrant identified by USG, unless when the abnormality was positioned along the periphery of two quadrants. In such cases, the location of the abnormality may be mapped to either of the quadrants, as it lies in the overlapped ROIs of two consecutive thermographic views. Thus, the maximum angular error of locating an abnormality is observed as $\pm 30°$ (1 view) with respect to camera position. In order to improve the accuracy of classification, the proposed system may be used as an adjunct to USG. Hence, curvelet transform-based texture features may be used to develop a reliable system for localization of breast cancer.

5 Conclusion

A comprehensive study has been conducted on the relatively new breast imaging technique: Rotational Breast Thermography to evaluate its performance for screening and characterization of abnormal breast conditions. As rotational breast thermography acquires images of the breast in multiple views, its ability for localization of abnormality has also been explored.

Features have been extracted and analyzed in spatial, wavelet, curvelet, and bispectral domains. These features have been used for detection of abnormality in rotational thermograms with a SVM classifier. It has been found that curvelet transform-based Haralick's texture features are best suited for the problem.

Screening performance of rotational thermography is found to be superior with curvelet-based texture features. As abnormal regions on breast thermograms exhibit curvilinear properties, curvelet transform-based feature extraction has resulted in better screening. Also a detected abnormality could be effectively characterized as benign or malignant. The ability of rotational thermography for detecting malignancy from normal and benign conditions has also been found to be effective.

GA has been used to identify three optimal features from the curvelet-based texture feature set. An improved system performance, screening accuracy of 94.4%, characterization accuracy of 95.8, and 100% sensitivity for malignancy detection, is achieved when these optimal features were used for classification. Localization of abnormality is a promising area for further research in rotational thermography.

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