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Cancer Detection in Rotational Breast Thermography Images using Bispectral Invariant Features

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ABSTRACT

Early diagnosis can increase the survival rate of women affected with breast cancer. Thermography is considered as an effective screening tool that is able to detect breast cancer ten years ahead of the traditional mammography methods. Highly sensitive infrared (IR) cameras capture the temperature and vascular changes of breasts and provide high-resolution diagnostic images of the same. But interpretation of thermograms is quite subjective in nature. Hence optimal features are needed to classify breast thermograms to help thermogram interpretation become more objective. In this paper, an automated approach to detect abnormalities in rotational breast thermograms is proposed. Breast region is segmented from the thermogram images. Bispectral invariant features are obtained from Radon projections of these images. These features are used to train a Support Vector Machine (SVM) classifier to classify unseen test images into normal, benign and malignant classes.

KEY WORDS: Thermography, Bispectral invariant features, Radon projections, Support Vector Machine (SVM) classifier.

1. INTRODUCTION

Breast cancer is the most frequently diagnosed form of cancer in women. It is also reported to be the second leading cause for mortality in women. The key to increase breast cancer survival rates is to detect it at the earliest possible stage. The technology of thermography is perfectly suited for early detection of breast cancer. It is the representation of the distribution of differences in temperature patterns on the skin due to any underlying pathology and the regional vascularization.

The basic principle of thermography is that metabolic activity and vascular circulation is higher in pre-cancerous tissues and the area surrounding the cancerous tissue than in normal tissues. The cancerous tumours recruit new vessels to increase blood circulation to their cells in order to supply nutrients. This leads to an increase in regional surface temperatures of the breast. Ultra-sensitive infrared cameras and computers are used in medical field to produce high quality images of these temperature variations. Due to the high sensitivity of infrared imaging, earliest indications of breast cancer can be observed.

The crucial part of any breast thermography detection system is the interpretation of the images. This can only be performed by a well-trained breast thermogram interpreter. The interpreter must analyze each thermogram and determine relevant thermal patterns and temperatures from non-relevant ones. This interpretation is based on training, experience and years of studies on thousands of women and hence is more subjective. The interpretation must always be confirmed by other standard means of testing. In order to improve the accuracy and reproducibility of thermogram interpretation, an optimal feature based system has to be developed for automatic classification. Several approaches have been proposed in the literature for the classification of breast thermograms.

Asymmetry analysis has been used for classifying breast thermograms by Pragati Kapoor (2012), and EtehadTavakol (2011). Acharya (2010), extracted texture features to detect abnormality in conventional thermograms using support vector machine (SVM). Bispectral invariant features have been proposed for diagnostic classification of breast thermal images by EtehadTavakol (2013).

Hossein Ghayoumi Zadeh (2011, 2012), proposed combinatorial model that consists of back propagation neural network and genetic algorithm; Adaptive Neuro Fuzzy Inference System (ANFIS) and genetic algorithm for diagnosing breast cancer. The potential of rotational thermography for detection of breast abnormality was analysed by Sheeja V Francis (2014). Bhavani Bharathi (2014), have studied the effectiveness of cold challenge in rotational thermography.

The objective of this work is to develop a breast cancer detection system using bispectral invariant features and SVM classifier. Firstly the breast thermogram images acquired from patients are analysed. The regions of interest (ROI) are segmented, followed by the extraction of bispectral invariant features. Next, the classifier is trained for automatically detecting breast cancer, so that the accuracy and reproducibility of thermogram interpretation may be enhanced.

2. METHODS & MATERIALS

Methodology

Image Acquisition: For taking rotational thermograms, special equipment called MAMRIT system (Mammary

Rotational Infrared Thermographic System) is used. It comprises of a highly sensitive IR camera inside an imaging chamber, integrated with inbuilt temperature control and monitoring system. A multi-axial rotating arm and positioning set up are enclosed within this closed chamber with a specially designed patient couch used for patient positioning on its top. The subject lies in prone position on MAMRIT system with one breast freely hanging through a small aperture. The infrared camera is fixed at the end of the multi-axial robotic arm. As the robotic arm rotates, the camera captures images of breast at different angles. Thus complete imaging of the breast is ensured (Bhavani Bharathi, 2014).

In rotational thermography, the breasts are imaged in the following order, viz., Left Pre-Cool, Left Post-Cool, Left Frontal, Right Frontal, Right Pre-Cool, Right Post-Cool. In each condition, a series of 12 images are obtained due to image capture at spatial intervals of 30 degrees. A temperature difference of 2 degrees is maintained between pre and post cool conditions, for the same breast, while ambient temperature is set according to the comfort level of each patient. The imaging is performed with informed consent of the patients and adhering to the approved protocol, using ICI7320P uncooled camera (Bhavani Bharathi, 2014). The work flow of the proposed method is shown in Fig.1

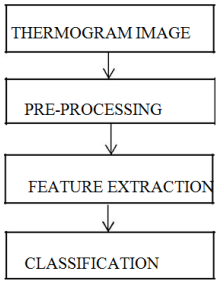

Figure.1. Work flow of the proposed method

Pre-processing: A sample normal image is shown in Fig. 2(a). The image contains the breast region along with the patient information and pseudo colour bar chart displaying temperature ranges. Such regions are removed from the complete image in order to obtain the breast region alone. Next, the central 30% area of the total breast is segmented as the ROI as shown in the Fig. 2(b). As ROIs are obtained in all 12 views, in this manner, complete breast is subjected to examination and no information is lost. The segmented region (in RGB) is converted to gray scale image and used for further analysis.

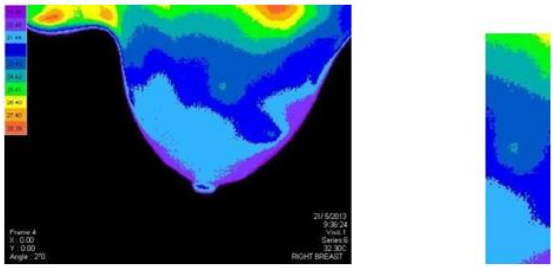

Figure.2. Normal Thermogram (a) Original image (b) Normal ROI

Similarly the pre-processed sample benign and malignant image is shown in Fig.3 and Fig. 4 respectively.

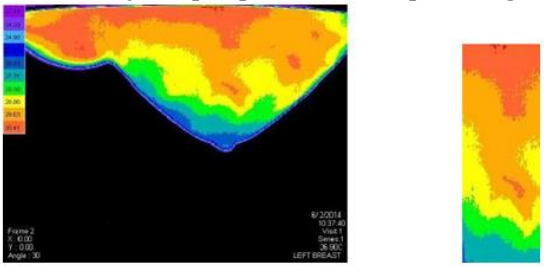

Figure.3. Benign Thermogram (a) Original image (b) Benign ROI

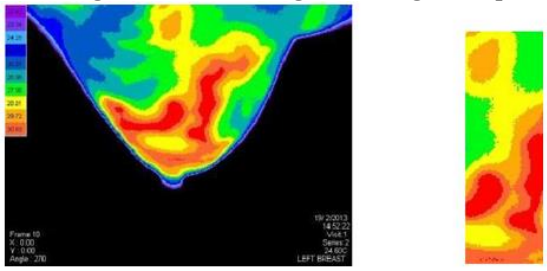

Figure.4. Malignant Thermogram (a) Original image (b) Malignant ROI

Feature Extraction: Feature extraction is the process of obtaining the set of features or image characteristics which will most efficiently represent the information that are important for analysis and classification. Bispectral Invariant features have been extracted in this study. These are third order spectral features which retain Fourier phase information and are more sensitive to shape changes. The bispectrum of a random signal x[k] can be defined in the frequency domain as in Eq.1

$$B(f_1, f_2) = X(f_1)X(f_2)X.(f_1 + f_2) \qquad (1)$$

where X(f) the Fourier transform of x[k], f is normalized frequency (divided by one half of the sampling frequency) that is between 0 and 1, * denotes the complex conjugate. The bispectrum is a function of two frequencies.

Due to its symmetry property, it needs to be computed only over a triangular region in bi-frequency space for a real-valued, discrete-time signal as shown in the Fig. 5

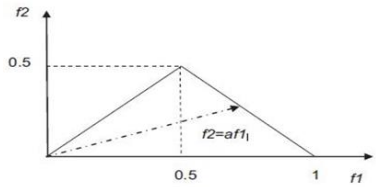

Figure.5.Region of computation of the bispectrum

The bispectrum *I(a)* is complex-valued and contains phase information as in Eq.,(2). The phase of the integrated bispectrum, also known as bi-spectral invariant feature, may be calculated along a straight line of given slope 'a', in bi-frequency space as *Ø(a) (*Mahnaz Etehad Tavakol, 2013) defined by Eq.3.

$$\mathrm{I}(a) = \int_{f1=0}^{\frac{1}{1+a}} \mathrm{B}(\mathrm{f}_1, \mathrm{af}_1)\mathrm{df}_1 = \mathrm{I}_{\mathrm{RS}}(\mathrm{a}) + \mathrm{jI}_{\mathrm{Im}}(\mathrm{a}) \qquad (2)$$

$$\phi(a) = \mathrm{arctam}\left(\frac{\mathrm{I}_{\mathrm{Im}(\mathrm{a})}}{\mathrm{I}_{\mathrm{RS}}(\mathrm{a})}\right) \qquad (3)$$

These features have been shown to be invariant to translation, scaling and amplification.

Classification: Support Vector Machine classifier (SVM) has been used for classification of normal and abnormal thermograms. The SVM is a supervised learning algorithm which constructs an N-dimensional hyper-plane for optimal separation of data into two categories. In SVM the input data is transformed to higher-dimensional feature space with the use of linear or non-linear kernel functions. Thus the transformed data becomes more separable compared to the original input data.

3. RESULTS AND DISCUSSION

Initialy, breast thermograms of 22 patients belonging to normal, benign and malignant classes were taken for analysis and bispectral invariant features were extracted from the ROIs. Radon Transform is used to reduce 2D image into a set of 1D parallel beam projections at various angles. Bispectrum is computed for each projection which is then integrated to give a complex value. The phase of the integrated bispectrum gives the bispectral invariant features. Thus each angle of projection yields a set of features. Totally 32 bispectral invariant features are extracted for eight projection angles, 0˚, 30˚, 45˚, 60˚, 75˚, 90˚, 120˚ and 135˚, with slope, a= ¼ , ½, ¾ and 1 for 22 normal, benign and malignant images and the result is shown in the Table 1.

The ability of each feature to discriminate between the various breast conditions was studied using paired t-test. Most of the features were found to be significant for normal versus benign and normal versus malignant experiments ($p < 0.05$) as shown in Table 2. Hence it is inferred that these features are able differentiate normal and abnormal breast conditions (i.e normal and benign; normal and malignant). Most of the features were found to be insignificant for benign versus malignant experiment ($p > 0.05$). Therefore it is inferred that these features do not differentiate between the abnormal conditions (i.e benign and malignant).

Table.1.Bispectral Invariant Features

Radon Projection Angles	Slope Normal Benign Malignant 'a'	Radon Projection Angles	Slope Normal Benign Malignant 'a'
0˚	¼ -0.0017 0.0080-0.0086	75˚	¼ -0.0612 0.1364 0.1003
	½ -0.0022 0.0104 -0.0100		½ -0.0671 0.1204 0.1048
	¾ -0.0025 0.0114 -0.0108		¾ -0.0717 0.1194 0.1089
	1 -0.0025 0.0114 -0.0107		1 -0.0666 0.10780.1009
30˚	¼ -0.0179 0.0344 0.0287	90˚	¼ -0.0469 0.1023 0.0750
	½ -0.0236 0.0428 0.0378		½ -0.0548 0.0977 0.0880
	¾ -0.0268 0.0473 0.0428		¾ -0.0593 0.0997 0.0942
	1 -0.0263 0.0459 0.0423		1 -0.0560 0.0917 0.0891
45˚	¼ -0.0330 0.0657 0.0524	120˚	¼ -0.0331 0.0700 0.0543
	½ -0.0419 0.0731 0.0652		½ -0.0407 0.0745 0.0689
	¾ -0.0475 0.0777 0.0723		¾ -0.0449 0.0784 0.0760
	1 -0.0461 0.0733 0.0696		1 -0.0431 0.0738 0.0733
60˚	¼ -0.0465 0.0972 0.0739	135 ˚	¼ -0.0170 0.0367 0.0319
	½ -0.0555 0.0966 0.0855		½ -0.0212 0.0449 0.0428
	¾ -0.0615 0.0995 0.0918		¾ -0.0234 0.0490 0.0482
	1 -0.0585 0.0915 0.0864		1 -0.0228 0.0475 0.0475

Table.2.Paired t-test for each class

Radon Projection Angles	Slope 'A'	Normal Versus Benign(p-value)	Normal Versus Malignant(p-value)	Benign Versus Malignant(p-value)
0°	¼	0.1053	0.1198	0.0082
	½	0.0808	0.1421	0.0071
	¾	0.0726	0.1431	0.0063
	1	0.0720	0.1419	0.0062
30°	¼	0.0000	0.0000	0.3756
	½	0.0000	0.0000	0.5316
	¾	0.0000	0.0000	0.6256
	1	0.0000	0.0000	0.6796
45°	¼	0.0000	0.0000	0.1859
	½	0.0000	0.0000	0.4908
	¾	0.0000	0.0000	0.684
	1	0.0000	0.0000	0.7756
60°	¼	0.0000	0.0000	0.1137
	½	0.0000	0.0000	0.4515
	¾	0.0000	0.0000	0.6514
	1	0.0000	0.0000	0.7536
75°	¼	0.0000	0.0000	0.0885
	½	0.0000	0.0000	0.4028
	¾	0.0000	0.0000	0.613
	1	0.0000	0.0000	0.7205
90°	¼	0.0000	0.0000	0.107
	½	0.0000	0.0000	0.5763
	¾	0.0000	0.0000	0.7775
	1	0.0000	0.0000	0.8874
120°	¼	0.0000	0.0000	0.2367
	½	0.0000	0.0000	0.7055
	¾	0.0000	0.0000	0.887
	1	0.0000	0.0000	0.9781
135 °	¼	0.0000	0.0000	0.5985
	½	0.0000	0.0000	0.8557
	¾	0.0000	0.0000	0.9485
	1	0.0000	0.0000	0.9998

These features are used to train the SVM classifier using leave-one-out method. In this method a single observation from the original sample is used as the validation data, while the remaining observations form the training data. This scheme is repeated until each observation in the sample has used once as the validation data. Three binary classification experiments were performed: normal versus benign, normal versus malignant and benign versus malignant and the performance of the classifier is analysed. The confusion matrix for each case is shown in the Table 3, Table 4 and Table 5 respectively.

Table.3.Confusion matrix for normal versus benign

		True Class	
		Normal	Benign
Detected Class	Normal	17 (Tn)	2 (Fn)
	Benign	5 (Fp)	20 (Tp)

- True Positive (TP): Benign classified as Benign.
- False Positive (FP): Normal classified as Benign.
- True Negative (TN): Normal classified as Normal.
- False Negative (FN): Benign classified as Normal.

Table.4. Confusion matrix for normal versus malignant

Detected Class	True Class	
	Normal	Malignant
Normal	16 (Tn)	4 (Fn)
Malignant	6 (Fp)	18 (Tp)

- True Positive (TP): Malignant classified as Malignant.
- False Positive (FP): Normal classified as Malignant.
- True Negative (TN): Normal classified as Normal.
- False Negative (FN): Malignant classified as Normal.

Table.5. Confusion matrix for benign versus malignant

Detected Class	True Class	
	Benign	Malignant
Benign	14(Tn)	9 (Fn)
Malignant	8 (Fp)	13 (Tp)

- True Positive (TP): Malignant classified as Malignant.
- False Positive (FP): Benign classified as Malignant.
- True Negative (TN): Benign classified as Benign.
- False Negative(FN): Malignant classified as Benign

Performance measures such as sensitivity, specificity and accuracy are evaluated for validation of binary classifications in computer-aided diagnosis. Sensitivity is the probability that a test will produce a positive result when used on diseased population. Specificity is the probability that a test will produce a negative result when used on disease free population. Accuracy is the proportion of true results (both true positive and true negative) in the population.

$$Sensitivity = \frac{TP}{TP + FN} \quad (4)$$

$$Specificity = \frac{TN}{TN + FP} \quad (5)$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (6)$$

The SVM classifier classifies the normal and benign breast conditions with accuracy of 84.09%, the normal and malignant breast conditions with accuracy of 77.27% and benign and malignant conditions with the accuracy of 61.36%. The sensitivity is found to be 90.91% for normal and benign breast conditions, 81.82% for normal and malignant breast condition and 59.10% for benign and malignant conditions while the specificity is found to be 77.27%, 72.73% and 63.64% respectively. When the data set was expanded to contain 36 cases in each class, accuracy rates improved as follows. Normal – Benign: 91.6 %, Normal – malignant: 90.3%, Benign – Malignant: 80.6% .

4. CONCLUSION

In the present work, performance of SVM classifier for automatic detection of breast cancer from rotational thermograms is analysed using the Bispectral invariant features. It is shown that these features are capable of differentiating between different normal, benign and malignant classes in breast thermograms. The SVM classifier has a better performance for classifying normal and abnormal breast conditions (i.e normal and benign; normal and malignant) while the performance is less among the abnormal condition (i.e benign and malignant). The accuracy of the classifier can be further improved by increasing the images for training the classifier and also by selecting optimal features. The future work focuses on collection of larger image database, feature optimisation and performance analysis of different classifiers.

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REFERENCES

Acharya UR, Ng EY K, Tan J H, Sree SV, Thermography based breast Cancer detection using Texture features and support vector machine', Journal of Medical Systems, 36, 2010, 1503-1510.

Bhavani Bharathi G, Sheeja V, Francis M, Sasikala, Sandeep D, Jaipurkar, Feature analysis for abnormality detection in breast thermogram sequences subject to cold stress, Proceedings of the National Conference on Man Machine Interaction, 2014,15-20.

Hossein Ghayoumi Zadeh, Javad Haddadnia, Maryam Hashemian, Kazem Hassanpour, Diagnosis of Breast Cancer using a Combination of Genetic Algorithm and Artificial Neural Network in Medical Infrared Thermal Imaging, Iranian Journal of Medical Physics, 9, 2012, 265-274.

Hossein Ghayoumi Zadeh, Omid Pakdelazar, Javad Haddadnia, Gholamali Rezai-Rad, Mohammad Mohammad-Zadeh, Diagnosing Breast Cancer with the Aid of Fuzzy Logic Based on Data Mining of a Genetic Algorithm in Infrared Images, Middle East Journal of Cancer, 3, 2011, 119-129.

Mahnaz Etehad Tavakol, Ng E.Y.K, Lucas C, Sadr I S, Gheissari N, "Estimating the mutual information between bilateral breast in thermograms using nonparametric windows, 35, 2011, 959-967.

Mahnaz Etehad Tavakol, Vinod Chandran, Ng E.Y.K, Raheleh Kafieh, Breast cancer detection from thermal images using bispectral invariant features, International Journal of Thermal Sciences, 69, 2013, 21-36.

Pragati Kapoor, Prasad S.V.A.V, Seema Patni, Image Segmentation and Asymmetry Analysis of Breast Thermograms for Tumor Detection, International Journal of Computer Applications, 50, 2012, 40-45.

Sheeja V, Francis M, Sasikala G, Bhavani Bharathi, Sandeep D, Jaipurkar, Breast cancer detection in rotational thermography images using texture features, Infrared Physics & Technology, 67, 2014, 490–496.

Vinod Chandran, Brett Carswell, Boualem Boashash, Steve Elgar, Pattern Recognition Using Invarients Defined from Higher Order Spectra, 2-D Image Inputs, IEEE Transactions on Image Processing, 6, 1997, 703-712.

Vinod Chandran, Stephen L, Elgar, Pattern Recognition Using Invarients Defined from Higher Order Spectra, One Dimensional Inputs, IEEE Transactions on Signal Processing, 41,1993, 204-212.