Assessment of Dynamic Infrared Images for Breast Cancer Screening using BEMD and URLBP

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Abstract

Thermal imaging is beneficial for early breast cancer diagnosis as it has the ability to measure even minute variation in blood vessels undetected by other imaging techniques. In the first phase of this work, frontal breast thermograms captured using dynamic protocol are pre-processed using anisotropic diffusion, registered and fused to obtain composite image. In the second phase, level-set segmentation is performed on the composite images to delineate Region of Interest (ROI). Further ROI images are subjected to Bidirectional Empirical Mode Decomposition (BEMD) and Uniform Rotated Linear Binary Pattern (URLBP) to obtain 59 feature vectors. Kernel Principal Component Analysis (KPCA) is implemented to select twenty significant feature vectors and the derived feature vectors are used as training and testing data set to the Least Square Support Vector Machine (LSSVM) classifier. Analysis is performed on 43 normal and 24 abnormal subjects chosen from database of mastology research. LSSVM using RBF kernel outperforms with high values of accuracy (86%), sensitivity (92%) and specificity (73%). Hence the proposed work can be used proficiently for early detection of breast cancer.

Key Words: Thermogram, Image Fusion, IMF, URLBP, LSSVM

1 Introduction

As per International agency for Research on Cancer’s (IARC) estimate, for every two women diagnosed with breast cancer, one woman dies of it making India as one of the effected country [1]. In India, over 1,00,000 new breast cancer cases are estimated to be diagnosed every year and has 17 percent of
world’s population suffering from it [2]. According to the statistics of World Health Organization (WHO), more than 60% of the women were identified with breast cancer at stage III or IV in India [3]. This drastically affected the survival rate and treatment choices for the patients. Hence there is a vital requirement for early detection of breast cancer.

Thermogram is a relatively new technology that has the capability of identifying abnormality using IR radiation emitted from the body surface. It is noninvasive, passive, painless making use of heat sensing camera to measure and map heat from the surface of breast and is suitable for women of all age groups. Cancerous and pre-cancerous cells exhibits high metabolic activity leading to increased regional surface temperature is picked by InfraRed (IR) camera. Infrared thermography has been proven to be a promising modality for early diagnosis of breast pathologies as it can identify abnormalities almost 8-10 years prior than any other procedure [4].

Anisotropic diffusion filtering is a nonlinear iterative process where edges are selectively smoothed based on the evaluation of the diffusion function. The diffusion coefficient is selected to vary spatially so as to encourage intra-region smoothing in preference to inter-region smoothing. It preserves edges and smooth's regions and is widely used in preprocessing stage making images more suitable for segmentation [5].

Image registration and fusion is an important and crucial process while considering multi-temporal, multi-view or multimodal images. Medical Image registration is a process of estimating geometric transformation for aligning images by means of one to one spatial mapping so as to maximize similarity between two medical images [6]. Image fusion fuses or combines all the aligned images so as to obtain composite image containing maximum information. It is commonly used for medical and satellite image processing applications [7].

Active contour or level set is an implicit deformable model implemented using simple finite difference scheme. Advantages of variational level set over traditional level set is that larger time step is used for solving partial differential equation hence speeding up curve evolution, maintains stable curve evolution, eliminates costly re-initialization process and is computationally efficient. Level set segmentation is commonly used for medical image segmentation [8, 9].

Empirical Mode Decomposition was originally introduced for signals (1D) but was extended to images (2D) and is known as Bidirectional Empirical Mode Decomposition (BEMD) or 2D Empirical Mode Decomposition (2D EMD). BEMD decomposes an image into set of bi-dimensional Intrinsic Mode Functions (BIMFs) based on local frequency information so that BIMF’s are locally orthogonal and a Bi-dimensional Residue (BR). BEMD process is data dependent with BIMF1 reflecting majority of the high frequency information representing edges and other points where there is huge variation in intensity. Also BIMF1 contains majority of information contained in input image and has high contrast compared to other BIMF’s, hence BIMF1 can be used alone for further analysis [10]. Local Binary Pattern (LBP) is a texture analysis approach that captures the local structure to provide efficient texture description but is not rotation
invariant. Hence Uniform Rotated Linear Binary Pattern (URLBP) is used to deal with rotation changes and uniformity in the pattern is utilized using dominant direction computed using index of neighboring pixel and weights in dominant reference direction to extract discriminative information [11].

Kernel Principal Component Analysis (KPCA) is a nonlinear form of dimensionality reduction technique that uses different kernel types to represent complicated data in a linear subspace effectively. Kernel PCA is computed using kernel matrix constructed from training data and eigenvalue decomposition of the kernel matrix [12]. Least square Support Vector Machine (LSSVM) is a supervised learning scheme that works with least square cost function, contains equality constrctions and the solution is obtained by solving set of linear equations. The capability of LSSVM is controlled by the choice of kernel function, requires less memory and is simple to implement compared to Support Vector Machine (SVM). LSSVM is used for both classification as well as regression [13].

2 Methodology

In this work, images are taken from Database of Mastology Research (DMR) containing dynamic frontal thermogram images acquired using FLIR SC-620 IR camera having a resolution of 640x480 pixels [14]. In dynamic acquisition protocol an initial procedure such as preparation of patient, maintaining room temperature and thermal cooling were followed to capture 20 image sequences during five minutes interval. Five dynamic images randomly chosen from twenty images of each subject are considered for the analysis. The dataset contains images from wide age group ranging from 29 to 85 years, containing breasts of different sizes such as medium, large and asymmetric breast size. Total number of subjects considered for analysis is 67 in which 43 normal and 24 abnormal subjects. Demographics of the subjects are as follows: Out of 43 normal subjects, 7 belong to an age group of 29-50 years, 31 belong to an age group of 51-70 years, 5 belong to an age group of 71-85 years and out of 24 abnormal subjects, 11 belong to an age group of 29-50 years, 12 belong to an age group of 51-70 years and 1 belongs to an age group of 71-85 years. The flow diagram representing framework for dynamic thermal image analysis is presented in fig.1.

![Flow diagram](image_url)

Figure 1: Framework for dynamic thermal image analysis

Input thermal images have low signal to noise ratio, less contrast and are very large in size. Thus the pre-processing steps such as conversion from RGB to grayscale, removal of unwanted regions such as neck arms and region below infra-mammary fold and image enhancement using anisotropic diffusion are applied to enhance the image quality. Anisotropic diffusion is the modified form of linear diffusion given by
\[
\frac{\partial g_t}{\partial t} = \text{div}[C(x,y,t) \nabla g_t(x,y)].
\]  

where \( g_t(x,y) \) is image at time \( t \), \( \text{div} \) represents divergence operator, \( \nabla g_t(x,y) \) is the gradient of the image and \( C(x,y,t) \) is conduction coefficient. Suitable choice of \( C \) is done to smooth intra-regions in the image and retain inter-region edges.

During dynamic thermal image acquisition patient may perform unintentional movements due to breathing or momentary imbalance causing differences in the acquired images. Hence image registration is performed on multi-temporal preprocessed dynamic thermal images considering first image as the reference image and remaining images are aligned with respect to this reference image. Image Registration consists of three components namely similarity metric, transformation and optimization. Similarity metric computes similarity between two images, optimizer defines the procedure for minimizing or maximizing the similarity metric and the transformation aligns misaligned image with respect to reference image. Fusion can be at pixel level, decision level or feature level. Fusion at pixel level is the simplest one wherein image fusion is performed in spatial domain operating directly on pixel intensity values.

Region of Interest (ROI) segmentation is performed on fused image using level set segmentation by providing few initial points around the desired ROI. Total energy for the level set function is given by

\[
\varepsilon(\phi) = \mu P(\phi) + \varepsilon_{\gamma,\nu}(\phi).
\]  

The term \( \mu P(\phi) \) represents internal energy that castigates the deviation of from a signed distance function during its evolution and an external energy term drives zero level set towards object boundaries and is represented by \( \varepsilon_{\gamma,\nu}(\phi) \). It is reported that 50 percentage of breast cancer is sited in pectoral region [16]. Hence care has been taken to include pectoral region along with breast region as ROI.

BEMD is performed on ROI in order to decompose an image into finite number of BIMF’s. The process of extracting the BIMFs one by one having the highest to the lowest local spatial variations of the data is known as sifting process represented in fig. 2. The sifting process concludes when the

\[
\text{SD between 2 consecutive shifting result} < 0.2
\]

Fig. 2. Shifting process
envelope mean is nearer to zero. The BEMD process is accomplished when there is no more extrema points present in the residue. Stopping criterion of sifting process can be obtained by restraining the size of the standard deviation calculated from two successive sifting results. In this process, BIMF1 has highest spatial variation containing majority of edge information sufficient to differentiate normal and abnormal images and hence is used alone for further analysis. Texture analysis is useful for quantitative analysis of breast thermogram and URLBP is one of the best texture analysis tool used due to computational simplicity and good performance. RLBP of a pixel with radius R in circular neighborhood and P number of neighbors is given by

$$RLBP_{g_r} = \sum_{p=0}^{P-1} s(g_{r_p} - g_{r_{c}})2^{mod(p-R,P)}. \tag{3}$$

where $g_{c}$ is gray-scale value of the center pixel, $g_{p}$ is gray-scale value of its neighbor, $p$ is the index of the neighbor, $R$ is the radius of the circular neighborhood and $P$ is the total number of neighbors. Uniform RLBP is computed using dominant direction. In URLBP, a look up table is used for mapping from binary to uniform pattern and for $P$ neighbors, $P(P-1)+3$ uniform patterns are obtained. URLBP is computed for BIMF1 to detect local features. Kernel PCA provides nonlinear mapping of input space into high dimensional feature space. The projection of eigen vector in feature space is given by

$$y_k(x) = \sum_{i=1}^{N} a_i (\phi (x), \phi (x)). \tag{4}$$

The second term represents symmetric kernel matrix computed from the training data set, avoiding inner product computation in high dimensional space thereby reducing the computation cost. KPCA is used for reducing dimension of URLBP based texture features from 59 to 20. Least square SVM is reformulation of standard SVM and the classification problem is formulated as

$$\min_{\omega, b, \epsilon} \frac{1}{2} \omega^T \omega + \frac{1}{2} \sum_{i} e_i^2. \tag{5}$$

LSSVM is subjected to equality constraint and classification is performed by solving linear set of equations. Least square SVM is trained using training set to learn the description for each texture class and is used to classify subjects as healthy and sick. Classification performance metrics such as Sensitivity (Sens), Specificity (Spec), Accuracy (Acc), Negative Predictive Value (NPV), Positive Predictive Value (PPV), F1 score, Youden’s Index (YD), Misclassification (MC) rate and AUC are computed for linear, RBF and Polynomial kernel functions [15], for varying values of $\sigma^2$ and regularization parameter $\gamma$. Finally the classifier is evaluated using confusion matrix and ROC.

3 Results and Discussion
In this work, dynamic frontal thermogram images (N=67) are taken from DMR database having a resolution of 640x480 pixels. Fig. 3(a)-(e) shows normal and fig. 4(a)-(e) shows abnormal dynamic frontal images.

Anisotropic diffusion is performed on cropped grayscale image to smooth intra-regions in an image and to retain edges. Number of iterations, n=15, conduction coefficient, c=20, λ=0.25 and an optional input is 1 to preserve high contrast edges. The pre-processed dynamic frontal images are aligned with respect to reference image using mutual information as metric, regular step gradient descent optimizer and affine transform and are fused using blending algorithm to obtain a composite image as shown in fig. 5(a) and fig. 5(b) for normal and abnormal case respectively.

Gradient $\nabla f$ is computed for the fused image to extract edge information is shown in fig. 6(a) and fig. 6(b) for normal and abnormal case respectively. Level set segmentation without re-initialization is applied on the obtained gradient image and binary mask is obtained by performing morphological dilation and closing operation using circular disk of radius 2 as structuring element. Finally the binary mask is multiplied with the pre-processed image; blank horizontal and vertical lines are removed to obtain final segmented ROI shown in fig. 7(a) for normal and fig. 7(b) for abnormal case. BEMD is performed on segmented ROI and standard deviation less than 0.2 is considered as the stop criterion to obtain IMF1, IMF2, IMF3 and a residue image as shown in fig. 8. URLBP is computed for IMF1, IMF2, IMF3 and residue with (P, R) = (8, 1) to detect local texture features and its corresponding histogram is shown in fig. 9. From the histogram it is evident that histogram of URLBP of IMF1 contains maximum information compared to IMF2, IMF3 and residue image. Hence 59 patterns representing
histogram of URLBP of IMF1 are considered for further processing.

Fig. 6. Gradient of fused images of (a) normal subject (b) abnormal subject

Fig. 7. Demarcated ROI images (a) normal subject (b) abnormal subject

Fig. 8. BEMD decomposition

Fig. 9. Histogram of URLBP for IMF1 to IMF3 and residue

Kernel PCA with polynomial kernel type having \( d = 0.0005 \) and reduced dimension as 20 is considered for dimensionality reduction as it provides better discrimination compared to other kernels. The reduced 20 URLBP features of IMF1 are passed through LSSVM classifier trained with 30 normal and 18 abnormal breast images and testing is performed on 24 normal and 11 abnormal subjects using linear, RBF and polynomial kernel. The performance of LSSVM is evaluated for different values of \( \sigma^2 \) for RBF kernel and different values of regularization parameter \( \gamma \) for all kernel types using leave one out cost function and are tabulated in table 1. From table 1, we can observe that RBF kernel (\( \gamma = 1 \) and \( \sigma^2 = 2.25 \)) provides superior performance compared to others. ROC curve and confusion matrix of RBF kernel with \( \gamma = 1 \) and \( \sigma^2 = 2.25 \) is shown in fig. 10 and fig. 11 respectively.

<table>
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<tr>
<th>Kernel</th>
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<th>( \gamma )</th>
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<th>Spec (%)</th>
<th>Acc (%)</th>
<th>PPV (%)</th>
<th>NPV (%)</th>
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Table 1. Performance measures for LSSVM

Fig. 10. ROC of LSSVM using RBF kernel (\( \gamma = 1 \) and \( \sigma^2 = 2.25 \))

Fig. 11. Confusion matrix of LSSVM using RBF kernel (\( \gamma = 1 \) and \( \sigma^2 = 2.25 \))
4 Conclusion

Breast cancer which is a challenging health issue can be detected at early stage by processing and analyzing set of dynamic thermal images using BEMD and URLBP. Using this approach, classification accuracy of 86% is achieved by LSSVM classifier using RBF kernel with $\sigma^2=2.25$ and $\gamma=1$. The accuracy of the system can be improved by using transform based fusion techniques and combining diverse group of features. The specificity of the system can be improved by processing and analyzing multimodal breast images. This work can be extended by combining static and dynamic images to identify suspicious region in the abnormal breast.

References
