Thermogram Breast Cancer Prediction Approach based on Neutrosophic Sets and Fuzzy C-Means Algorithm

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Abstract— **The early detection of breast cancer makes many women survive. In this paper, a CAD system classifying breast cancer thermograms to normal and abnormal is proposed. This approach consists of two main phases: automatic segmentation and classification. For the former phase, an improved segmentation approach based on both Neutrosophic sets (NS) and optimized Fast Fuzzy c-mean (F-FCM) algorithm was proposed. Also, post-segmentation process was suggested to segment breast parenchyma (i.e. ROI) from thermogram images. For the classification, different kernel functions of the Support Vector Machine (SVM) were used to classify breast parenchyma into normal or abnormal cases. Using benchmark database, the proposed CAD system was evaluated based on precision, recall, and accuracy as well as a comparison with related work. The experimental results showed that our system would be a very promising step toward automatic diagnosis of breast cancer using thermograms as the accuracy reached 100%.**

I. INTRODUCTION

Breast cancer is the most common cancer among women in the world. In the USA, one death of women out of four is due to breast cancer [1]. Mammogram is one of the most imaging technology for diagnosing breast cancer. Although mammogram has recorded a high detection and classification accuracy,it is difficult in imaging dense breast tissues, its performance is poor in younger women and harmful, and it couldn't detect breast tumor that less than 2 mm [2].

Infrared thermography (IRT) is used in production control as well as several fields of science like building diagnosis [3]. The main idea of IRT is that, it detects infrared light which is emitted by an object. For example, if the object is a person's body the IRT camera visualizes any changes in this body's heat caused by abnormalities in the blood flow existed in the surface of diseased areas [4]. IRT does not considered tool which illustrates anatomical abnormalities, but it is a method showing physiological changes. This method has been used for the first time for breast cancer started in [5] and has proved its accuracy for early detection, where tumor regions are usually higher in temperature than other regions. Thermography is not better than mammography in terms of specificity but it is non-invasive functional imaging method which is harmless, passive, fast, and low cost [4].

In the early use of infrared images in the detection/diagnosis of the breast cancer [5], it faces many challenges such as poor calibrated equipment and low capability [5], [6]. Later in the 90's [7], it was reported that with the advances of the infrared imaging technology, IRT could be a good source of images to study and detect the cancer at the early stages. Since then, crucial attentions have been directed to the thermal images again as a good mean to detect the breast cancer. The main advantage of IRT with breast cancer is that the early detection which is crucial for cancer patients for increasing the percentage of survival.

Several Computer-Aided Detection(CAD) systems were proposed, e.g. [8], [9], [10], [11], [12]. These systems can be manual, semi-automatic or fully automatic process [13]. Typically, CAD systems is initiated by segmenting thermogram image to obtain a region of interest (ROI), then some features are extracted and finally classification algorithms are used to classify the breast to normal or abnormal [8]. For this purpose, different features have been tested. Texture features were used to detect abnormal thermograms using support vector machine (SVM) [9] and artificial neural networks [10]. Wiecek et al. [12] used features based on Discrete Wavelet Transform (DWT) with biorthogonal, Haar mother wavelets, and neural networks to classify thermograms.

In this paper, we present an approach for automatic classification for thermogram to normal and abnormal. This approach consists of two main phases: (1) automatic segmentation done by Neutrosophic sets in conjunction with fuzzy c-means to get ROI; (2) classification achieved by extracting features, i.e. statistical, texture and energy, and then classified by SVM to into normal and abnormal.

The remainder of this paper is organized as follows. Section II discuss the related work and Section III presents the proposed CAD approach. In Section IV, the experimental results and discussion are given. Finally, the conclusion and future work are discussed in Section V.

II. RELATED WORK

To make our proposed approach comparable with its related work, we will present previous efforts done using the PROENG database [14]. These efforts can be classified into: automatic segmentation of breast regions [8], [15] and classification based on the asymmetry analysis to normal and abnormal cases [16], [17], [18].

For the automatic segmentation [8], [15], the level set technique [19] has been used to extract the blood vessels in a thermal image. The Level set function was evolved using the gradient magnitude and direction of an edge map provided by few initial points selected in region of interest. In [8], an automatic segmentation approach, using active contour and level set method without re-initialization, was proposed to extract the breast regions from breast thermograms. Before

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applying the level set, a statistical based noise removal technique and contrast limited adaptive histogram equalization were used to improve signal to noise ratio and contrast of thermal images. Verification and validation of the segmented results were carried out using 60 images against the ground truths. The segmented areas were observed to be in good correlation with the ground truth areas as the correlation coefficient was 98%.

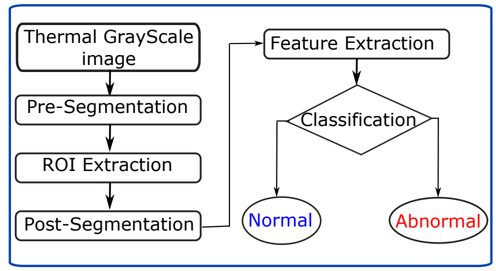
Another automatic segmentation approach has been proposed in [15] to segment the frontal breast tissues from breast thermograms. This approach made use of the Modified Phase Based Distance Regularized Level Set (MPBDRLS) method. The method was further modified by adopting an improved diffusion rate model. The segmented region of interests was evaluated using 72 gray scale images of size 320 x 240 pixels and against the ground truth images. The overlap measures showed that the average similarity between four sets ground truths and segmented region of interests was 97%.

The asymmetric-based classification is based on the asymmetric abnormalities which can be identified by comparing the features extracted from the breast regions (right and left). Several statistical and fractal features are found to be useful features in identification of pathological conditions of breast tissues [18]. Using PROENG database, in [16], an approach was proposed to classify the normal and abnormal (carcinoma, nodule and fibro adenoma) breast thermograms Gabor wavelet transform. First, the segmentation of the breast tissues was performed using ground truth masks and the raw images. Gabor features were then extracted for the detection of the abnormalities. The results showed that from total of 20 images, used of the approach evaluation, there were 9 images with carcinomas, 6 with nodules, and 5 with fibro adenomas.

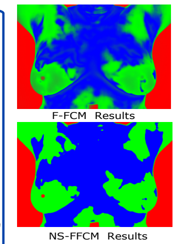
In [17], another asymmetry analysis for breast thermograms was proposed using non-linear total variation diffusion filter and reaction diffusion based level set method. Initially the images were subjected to total variation (TV) diffusion filter to generate the edge map. Reaction diffusion based level set method was then employed to segment the breast tissues using TV edge map as stopping boundary function. Asymmetry analysis is then performed on the segmented breast tissues using wavelet based structural texture features. The evaluation of this approach was done using 20 images that have pathologies either in left or right region. The results of this approach showed that the segmented area of TV based level set is correlated with the ground truth with 99%.

FCM and Fast-FCM [20] has been applied and proven to be good for image segmentation as they retain more information than that of the hard segmentation methods. However, as reported in [21] the indeterminacy of each element in the FCM and F-FCM could not be evaluated and described and in some applications, e.g, expert system, the indeterminacy should be considered.

Neutrosophic sets (NS) can be used to address this problem. NS introduces a new component called "indeterminacy" which carries more information than fuzzy sets do [22]. Therefore, applying the Neutrosophic sets based on F-FCM



(a) Stages of the proposed CAD system



(b) FFCM vs NS-FFCM

(NS-FFCM) algorithm to the segmentation process of thermal breast cancer images may allow achieving both vital important goals at once. Figure (1b) illustrates the effect of NS comparing to F-FCM only.

III. THE PROPOSED CAD SYSTEM

The proposed CAD system for thermogram images, as shown in Figure (1a), consists of six steps which are explained below.

Thermogram image transformation: Thermogram images are firstly pre-processed using median filter to remove any noise, resulted in by defects of the IRT camera [23]. Then, as illustrated in Algorithm(1), the images were transformed to neutrosophic domain to reduce the indeterminacy degree of the image, which is evaluated by the entropy of the indeterminate subset. Then, the image becomes more uniform and homogenous, and more suitable for segmentation.

Algorithm 1 Neutrosophic sets transformation approach

1: Given a grayscale image G of size (M x N), initiate a neutrosophic image P_{NS} of the same size.
2: Each pixel in P_{NS} is represented by three subset T ,I and F. $PNS(i,j)$ =$T(i,j)$, $I(i,j)$, $F(i,j)$, where $T(i,j)$, $I(i,j)$ and $F(i,j)$ are the probabilities belong to white set, indeterminate set and non-white set, respectively.
3: Compute histogram of the image.
4: Compute the mean and local maxima of the histogram.
5: Find peaks greater than the mean of local maxima.
6: Compute $T(i,j)$ from the first peak be g_{min} and the last peak be g_{max}, i.e. local of the mean window.
7: Compute $I(i,j)$ from the homogeneity value of T using the absolute value of the difference between intensity $g(i,j)$ and its local mean value.
8: Compute$F(i,j)$= 1-$T(i,j)$.
9: Compute the entropy of each band, En_T for T, En_I for I and En_F for F.
10: Compute the Entropy En_{NS} to evaluate the NS image for T, I, F where En_{NS}=En_T+En_I+En_F

Pre-, segmentation and Post-segmentation: Pre-segmentation processes are done by decreasing the indeterminacy set and removing the noise. The image became more uniform, homogenous, and more suitable for clustering using optimized F-FCM which was applied to cluster the thermal NS image to three clusters: red background, blue for body tissue, and green for the breast tissue, see Fig. (2). To obtain F-FCM rather than FCM, the histogram of the image intensities is used during the clustering process instead of the raw image data to increase the computation efficiency.

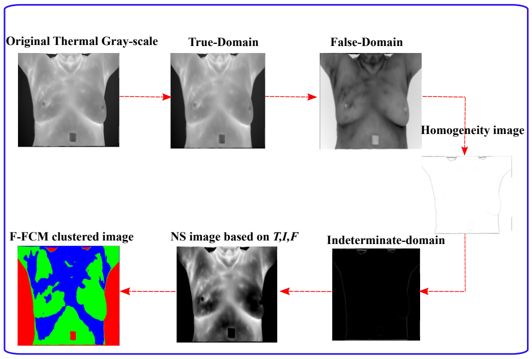


Fig. 2: Results of clustering thermal image using NS sets and F-FCM

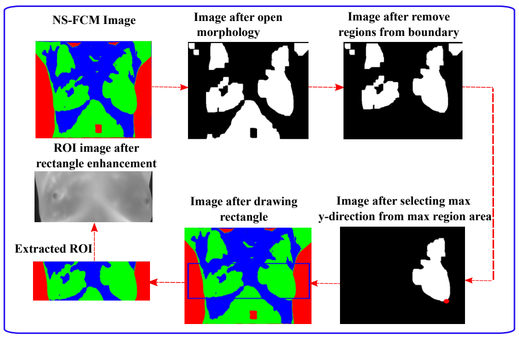


Fig. 3: Steps of the Post-segmentation algorithm to detect and segment abnormal breast parenchyma from thermal NS-FFCM image.

Post-segmentation algorithms, as explained in Algorithm (2), were used to enhance the segmentation results and remove non-ROI.

Algorithm 2 Pre and post segmentation process

1: Segment *NS* image by using Fast Fuzzy c-means.
2: Resize each channel of the enhanced image to 512x512
3: Convert green channel of enhanced image to binary image using Ost'u thresholding
4: Apply opening morphology operator to disconnect breasts region from other body area
5: Remove regions that connected to the image boundary (shoulders and stomach area).
6: Get max ROI using Connected component algorithm (CCL)
7: Trace boundary of this ROI to get max y-direction
8: Draw rectangle given these points
9: Enhance rectangle and focus on the body area through delete background regions with low intensity values.
10: Use coordination of rectangle on original gray-scale image

Feature Extraction: A number of feature extraction techniques, GLCM, Gabor filter, and first statistics, were applied to the segmented image. 30-features were extracted: 22 from GLCM [11], 3 from absolute Gabor coefficients [16], and 5 from first order statistics.

Classification Phase: To classify the extracted features, the SVM classifier was used. It is a supervised learning method that transforms input data to high-dimensional feature space though different kernel functions: e.g. Linear, polynomial, RBF, and quadratic [24].

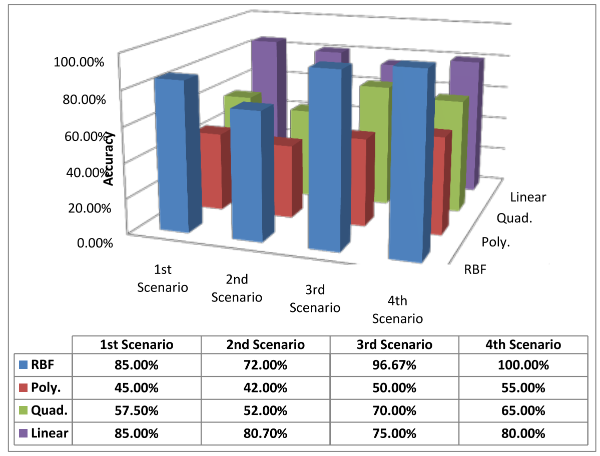


Fig. 4: The accuracy of the SVM classifier using different kernel functions for the 4 scenarios.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A benchmark database [14] was used to evaluate our proposed approach. It was contains 149 patients with images at size of 640×480 pixels. The frontal images are selected to test the proposed CAD system. 63 cases, 29 healthy and 34 malignant, are used.

In order to prove the robustness of the proposed system, as illustrated in Table (I), four scenarios were evaluated using the SVM classifier. They were designed to understand the stability of the proposed system under different conditions. The results of the four scenarios using SVM kernel functions (linear, RBF, Polynomial, and Quadratic) are summarized in Fig. (4). In addition to the accuracy evaluation, we used, as demonstrated in Table (II, III, and IV), the Precision, Recall, and Error rate respectively, for the results evaluation. Further evaluation, as seen in Figure (5) was done using the "leave-one-out" approach Comparing with the related work in [16], [17], [18], our proposed system achieved better accuracy, reaching 100 %, while using a higher number of images for testing and training. This is due to the automatic extraction and enhancement of the ROI.

TABLE I: Different scenarios for training and testing the system

Scenarios	Training Data		Testing Data	
	Normal	*Abnormal*	*Normal*	*Abnormal*
1^{st} Scenario	13	10	16	24
2^{nd} Scenario	8	5	21	29
3^{rd} Scenario	14	19	15	15
4^{th} Scenario	19	24	10	10

As shown from Table (II, III, and IV), it can be noticed that (1) the more training images were used, the high accuracy was obtained as the case of the *4th scenario* reaching 100%; (2) the RBF-SVM classifier gave the best results for classifying thermogram images .

TABLE II: The precision evaluation of the results

Scenarios	Precision			
	Quad.	*Poly.*	*RBF*	*Linear*
4^{th} Scenario	80%	100%	100%	15%
1^{st} Scenario	68.75%	NaN	93.75%	78.95%
2^{nd} Scenario	48%	42.11%	81.25%	62.50%
3^{rd} Scenario	45.45%	42%	76.92%	76.19%

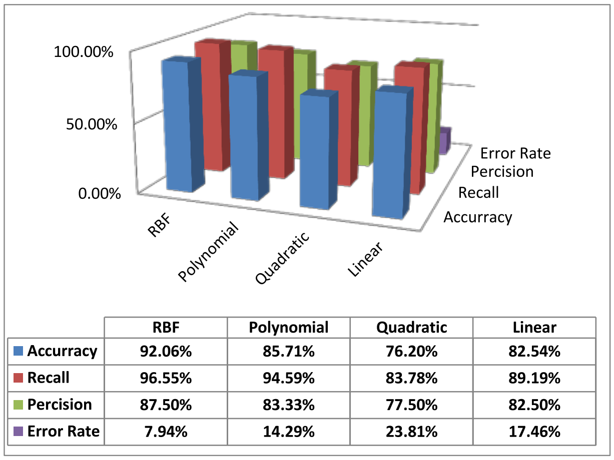


Fig. 5: Results of the Leave-One-Out Cross-Validation Method

TABLE III: The Recall evaluation of the results .

Scenarios	Recall			
	Quad.	*Poly.*	*RBF*	*Linear*
1^{st} Scenario	40%	10%	100%	90%
2^{nd} Scenario	73.33%	0%	100%	100%
3^{rd} Scenario	75%	100%	81.25%	93.75%
4^{th} Scenario	71.43%	100%	47.62%	76.19%

TABLE IV: The error rate evaluation of the results.

Scenarios	Error Rate			
	Quad.	*Poly.*	*RBF*	*Linear*
1^{st} Scenario	35%	45%	0%	81.18%
2^{nd} Scenario	30%	50%	3.33%	13.33%
3^{rd} Scenario	42.50%	55%	15%	25%
4^{th} Scenario	48%	58%	28%	20%

V. CONCLUSION AND FUTURE WORKS

In this paper we proposed a CAD system for thermogram breast images. The system first extracted ROI using Neutrosophic Set, F-FCM and morphological operators. It then used several features (statistical, texture and energy) with the SVM to detected normal and abnormal breast. Using a benchmark database, the proposed system was evaluated through recall, accuracy, precision, and error rate showing that our CAD system achieving an excellent results. Also, it was found that NS sets with F-FCM is an effective segmentation method for thrmogram images as NS enhanced thermal image and reduced the indeterminacy. In the future, we plan to evaluate our system using a large size of the dataset to test its reliability.

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