

Classification of Mammographic Micro calcification Clusters

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Abstract— Goal: The presence of microcalcification clusters is a primary sign of breast cancer; however, it is difficult and time consuming for radiologists to classify microcalcifications as malignant or benign. In this paper, a novel method for the classification of microcalcification clusters in mammograms is proposed. **Methods:** Morphology, FCM are the two algorithms used to detect the tumour by its time, area, accuracy, sensitivity and specificity. The parameters used in these two algorithms shows variation in detecting the tumour. **Results:** The validity of the proposed method is evaluated using MIAS (Mammographic Image Analysis Society). A full comparison of time, area, accuracy, sensitivity and specificity is done relatively to all algorithms. **Conclusion:** The results indicate that the proposed approach is able to outperform the current state-of-the-art methods. **Significance:** This study shows that morphological modeling is an important tool for microcalcification analysis not only because of the improved classification accuracy but also because the parameters like time, area, accuracy, sensitivity and specificity can be linked to clinical understanding.

Index Terms—Classification, graphs, mammography, microcalcifications, morphology, FCM.

I. Introduction

BREAST cancer is currently the most common cancer affecting women worldwide. In women, it is the leading cause of cancer death 89% of the women are likely to survive for at least 5 years. In India 70,218 women died of breast cancer in 2012 and deaths from the disease are predicted to increase to 76,000 in 2020 with an average age of incidence shifting to 30 years from 50 years. Mammography is one of the most reliable and effective methods for detecting breast cancer at its early stages. In developed countries, population-based mammography screening programs have been implemented. Women are encouraged to participate in regular breast examinations through mammography. In the U.S., annual mammographic screening is recommended for women at normal risk, beginning at age 40. In the U.K., women aged between 50 and 70 years are invited for breast

screening every three years. Microcalcifications are small deposits of calcium salts within breast tissue that appear as small bright spots in mammograms. The presence of microcalcification clusters is a primary sign of breast cancer. The radiological definition of a microcalcification cluster is an area of 1 cm² that contains, in general, no fewer than three microcalcifications. The spatial resolution of mammography is very high (normally in the range of 40–100 μm per pixel), and therefore, mammography enables the detection of microcalcifications at an early stage. However, not all microcalcification clusters necessarily indicate the presence of cancer, only certain kinds of microcalcifications are associated with a high probability of malignancy.

Mammographic Image Analysis Society (MIAS) database, containing a malignant microcalcification cluster and a benign microcalcification cluster, respectively. In clinical practice, it is difficult and time consuming for radiologists to distinguish malignant from benign microcalcifications. This results in a high rate of unnecessary biopsy examinations. In order to improve the diagnostic accuracy of radiologists interpreting microcalcifications in mammograms, computer-aided diagnosis (CAD) systems have been applied to reduce the false positive rate (FPR) while maintaining sensitivity. Many methods for CAD of microcalcifications in mammograms have been proposed. A variety of features have been studied in the literature to characterize microcalcifications and classify these abnormalities into malignant and benign, such as shape, morphological, cluster, intensity-based, and texture features. Early research showed how the morphological characteristics of microcalcifications could be used to differentiate between malignant and benign cases. The shape and morphological features are mainly extracted from individual microcalcifications and describe the morphological characteristics of individual microcalcifications, such as roughness, size, and shape. Complementary to the shape and morphological features, cluster features concentrate on the global properties of microcalcification clusters. Some were used to describe the morphology of microcalcification clusters, such as cluster area, cluster perimeter, cluster diameter, cluster circularity, cluster eccentricity, and cluster elongation. Others were intended to capture the spatial distribution of individual microcalcifications within a cluster, such as average and standard deviation of distances between microcalcifications. In addition, a novel model-based method was presented to reconstruct and analyze microcalcification

clusters in 3-D from two mammographic views. Although a broad variety of techniques for CAD of breast cancer have been developed in the past two decades, some of which have achieved a high sensitivity and specificity for specific abnormalities, the automatic and accurate classification of microcalcification abnormalities as malignant or benign remains a challenge due to their inherent nature; furthermore, most of the existing approaches have their own specific disadvantages.

First, for the approaches based on the shape/morphology of individual microcalcifications, informative features cannot be attained when microcalcifications are very small (occupying only a few pixels) so that it seems meaningless to analyze the shape/morphological properties of such small objects. Second, microcalcifications may have very low contrast with respect to the surrounding tissue especially when microcalcifications form within dense tissue which has high and homogeneous intensity. As such, the lack of useful texture information within the background region affects the capability of the approaches based on the intensity variations and texture features. In addition, for the approaches describing the spatial distribution

of microcalcifications within a cluster, the global cluster features were computed based on a fixed resolution, and the distance-based features rely on the original spatial resolution of mammography. This results in a lack of robustness and adaptiveness to different spatial resolutions of mammograms in particular screen-film mammograms acquired by different digitizers. According to some studies on the evaluation of breast microcalcifications, malignant microcalcifications tend to be small, numerous (>5 per focus within 1 cm^2) and densely distributed

because they lie within the milk ducts and associated structures in the breast and follow the ductal anatomy. However,

benign microcalcifications are generally larger, smaller in number ($<4 - 5$ per 1 cm^2) and more diffusely distributed

as these microcalcifications arise within the breast stroma, benign cysts or benign masses. These differences result in variations in the distribution and closeness of microcalcifications

within the clusters and provide radiologists with information which enables decisions regarding the need for further assessment and possible breast biopsy. Hence, we propose a novel method for modeling and classifying microcalcification clusters in mammograms based on their topological properties. The topology of microcalcification clusters is analyzed at multiple scales using a graph-based representation of their topological structure. This method is distinct from existing approaches that mainly concentrate on the morphology of individual microcalcifications and only compute the distance-based cluster features at a fixed scale. In this method, a set of topological features are extracted from microcalcification graphs at multiple scales, and a

multiscale topological feature vector is subsequently generated to discriminate between malignant and benign cases. A preliminary version of this study has been reported in, where the idea of analyzing microcalcification clusters using their topological structure is initially investigated based on a small number of cases. In this paper, the evaluation has been extended by including additional data (from several databases). We have also investigated the effect of variation in microcalcification

segmentation, the dataset size, the individual significance of eight graph metrics for malignancy diagnosis, and a direct comparison with state-of-the-art methods.

II. Methodology

We propose to relate the time, area, accuracy, sensitivity and specificity of tumour detection through morphology and FCM algorithms. The input

image (left or right is considered) is aligned to either left or right. Then unwanted portions like time, date, year of the image are removed. Pectoral muscle connecting shoulders and chest is removed using pectoral code. The importance of the pectoral removal is that it interferes with the detection of tumour as it has high intensity. Pectoral code consists of threshold value 0-255 to detect pectoral muscle and to remove it. Pectoral muscle is continuous in intensity so the threshold value is also high. By this method we can detect and remove the pectoral muscle. To extract the pectoral muscle both the area of pectoral muscle and affected area are subtracted. The resultant image after applying pectoral code is given to the morphology and FCM algorithms.

A. Morphology Algorithm

Morphology deals with forms or structures of animals and plants. Morphology algorithm undergoes sharpening, smoothing and filtering. It is done using binary values. Erosion and Dilation are the basic techniques in morphology algorithm. Decrease in boundary area is erosion and increase in boundary area is dilation. Criterion function is used for

morphology based tumour segmentation (clustering). Criterion function is given by multiplying infinity with the ones of the pixels. Infinity refers to positive number or overflow (eg: $\exp 1000$). The resultant image is divided into two histograms, histogram1 and histogram2 having threshold values 0 to 150 and 150 to 240 respectively. Pixel1 and pixel2 are the sum of values of histogram1 and histogram2 respectively. If both the pixel values are greater than zero then criterion function (with threshold value) is calculated for clustering.

B. FCM (Fuzzy c-means clustering)

This algorithm works by assigning membership to each data point corresponding to each cluster center on the basis of distance between the cluster center and the data point. More the data is near to the cluster center more is its membership towards the particular cluster center. Clearly, summation of membership of each data point should be equal to one.

Algorithmic steps for Fuzzy c-means clustering

Let $X = \{x_1, x_2, x_3 \dots, x_n\}$ be the set of data points and $V = \{v_1, v_2, v_3 \dots, v_c\}$ be the set of centers.

1) Randomly select 'c' cluster centers.

2) Calculate the fuzzy membership ' μ_{ij} ' using:

$$\mu_{ij} = 1 / \sum_{k=1}^c (d_{ij} / d_{ik})^{(2/m-1)}$$

3) Compute the fuzzy centers ' v_j ' using:

$$v_j = (\sum_{i=1}^n (\mu_{ij})^m x_i) / (\sum_{i=1}^n (\mu_{ij})^m), \forall j = 1, 2, \dots, c$$

4) Repeat step 2) and 3) until the minimum 'J' value is achieved or $\|U^{(k+1)} - U^{(k)}\| < \beta$.

where,

'k' is the iteration step.

' β ' is the termination criterion

between

[0, 1]. ' $U = (\mu_{ij})_{n \times c}$ ' is the fuzzy membership

matrix.

'J' is the objective function

C. Parameters (Time, Area, Accuracy, sensitivity and specificity):

Time, Area, Accuracy, sensitivity and specificity are the five parameters used in both morphological and FCM algorithm to get better performance and accuracy.

a. Time

Time is the execution time taken for result and is calculated using tic and toc is a stopwatch timer. Area is the area of the tumour.

b. Area

Area(X,Y) produces a stacked area plot suitable for showing the contributions of various components to a whole. For vector X and Y, AREA(X,Y) is the same as PLOT(X,Y) except that the area between 0 and Y is filled. When Y is a matrix, Area(X,Y) plots the column of Y as filled areas. For each X, the net result is the sum of corresponding values from the columns of Y. AREA(Y) uses the default value of X=1:SIZE(Y,1).

c. Accuracy

Accuracy is one of the most important parameter for best results. By forming the curve of the area of tumour, accurate results can be obtained.

d. Sensitivity

Sensitivity is done using far(false acceptance rate). False acceptance rate is the measure of likelihood that is accepted incorrectly. False acceptance rate is the **ratio** of the number of false acceptances divided by the number of identification attempts. False acceptance rate is done few times and compared to detect the sensitivity.

e. Specificity

Specificity is done using frr(false rejection rate). False rejection rate is the measure of likelihood that is rejected incorrectly. It is the **ratio** of the number of false rejections divided by the number of identification attempts. False rejection rate is done few times and compared to detected the specificity.

III. Conclusion

We have presented a method for classifying microcalcification clusters in mammograms based on morphological and FCM based analysis. This is a novel approach to analyze microcalcifications in terms of dilation and erosion for discriminating malignant from benign clusters. A set of parameters are analyzed using these two morphology and FCM algorithms like time, area, accuracy, sensitivity and specificity. Resulting in the malignancy of cancer with the tumour area and its sensitivity are recommended to physicians. A table consists of time in secs, area in sq mm, accuracy, sensitivity and specificity. All these parameters are really very helpful to detect the cancer earlier with accuracy. In proposed system, the Morphology and FCM algorithm results are used to detect the microcalcifications by histogram adaptive thresholding technique to get higher performance and accuracy. Earlier detection is very important for proper treatment. So, this system can obtain such results to provide solution for tumour.

