Classification of Clustered Microcalcifications in Mammograms Using Graph Method

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Abstract – Novel method for the classification of micro calcification clusters in mammograms is proposed Methods. The topology/connectivity of individual Morphology of micro calcification clusters, such as cluster area, cluster perimeter, cluster diameter, cluster circularity, cluster eccentricity, and cluster elongation. The radius of the structuring element is equal to 6 pixels (i.e., scale=6). The boundaries of dilated micro calcifications are displayed using different colors and each individual micro calcification is labeled with a sequential number which is ordered according to the spatial location of the corresponding micro calcification in the image patch. A set of micro calcification graphs were constructed to describe the topological structure of micro calcification clusters at multiple scales. In a micro calcification graph, each node represents an individual micro calcification, and an edge between two nodes is created if the two corresponding micro calcifications are connected or overlap in the 2-D image plane. Artificial Neural Network (ANN)-based classifiers are used for classifying micro calcification clusters into malignant and benign.

Index Terms – MCC- Micro calcification, ANN- Artificial Neural Network, GUI- Graphical User Interface.

1. INTRODUCTION

Micro calcifications (MCCs) generally present an early sign of breast cancer. According to related medical reports, although clustered MCCs associated with benign and malignant disease usually have distinct characteristics. This creates diagnostic interpretation difficulty. Under such circumstance, most radiologist encourage biopsies, even only 20-30% of cases are found to be cancer. Thus decreasing the false-positive biopsy rate for mammographic ally detected abnormalities is important in image analysis of calcifications in mammograms. It also presents a challenge for radiologists who only recognize the presence of MCCs, but also assess the likelihood of malignancy in order to avoid unnecessary biopsies. The difficulties in MCCs diagnosis arise primarily in that the characteristic differences between benign and malignant. The report reveals that both stages benign and malignant are achieve 100% correct classification rate. Mammography is the most sensitive method for detection of early breast cancer. Microcalcificationare small deposits of calcium in breast tissue that appear as small bright spots in mammograms. The presence of micro calcification clusters within a mammographic image is a primary sign of breast cancer. The radiological definition of a micro calcification cluster is an area of1 cm2 that contains more than 5 micro calcifications.

2. RELATED WORK AND PROPOSED MODELLING

The connectivity between the individual micro calcification is estimated by performing morphological dilation at multiple scales. The scale corresponds to the radius of the structuring element measured in pixels. As the scale increases dilation absorbs nearby pixels into individual micro calcifications. Therefore the connectivity between micro calcifications within the cluster is varied by the multi scale dilation. As the scale increases the connectivity will be higher for dense distribution and it will be lower for the wide distribution.

2.1. COLOR SPACE

It is quite natural idea to use color to detect human body because color is one of the most remarkable features of human bodies. However the color of body surface is prone to be affected by many factors such as light source, touch, shadow and occlusion caused by different angles of lighting. Thus, on the other slide, it is also a very challenging task to segment human body using color information. In real application the issue still needs to solve that in which color space the skin color can cluster well. In fact, different color spaces are different expression of color in computer and each color space has its specific application field and background of generation.

2.2 RGB COLOR SPACE

The RGB color model, the name of which comes from the initials of the three additive primary color red, green and blue, is an additive color model in which three primary color are added together in various ways to reproduce a broad array of color. Though the RGB color model was used in conservational photography initially, the major current purpose of this model is to sense, represent and display image in electronics systems, such as computers and televisions.

2.3. LAB COLOR COMPONENT

The LAB color model is a three axis color system and LAB colors are absolute, meaning that the color is exact. It's what's known as device independent; meaning that the LAB color space is the only way to communicate different colors across different devices. An object's color is measured in LAB color with a spectrophotometer. It is a three axis system. The first axis, the L-channel or Lightness, goes up and down the 3D color model and it consists of white to black – and all of your gray colors will be exactly right down the center. All neutral colors will be relatively in the center of this axis. and the second axis is A, goes from cyan color across to magenta/red color. And the third one is B axis goes from blue to yellow.

2.4. BINARY IMAGE

For a binary image, white pixels are normally taken to represent foreground regions, while black pixels denote background. (Note that in some implementations this convention is reversed, and so it is very important to set up input images with the correct polarity for the implementation being used). Then the set of coordinates corresponding to that image is simply the set of two-dimensional Euclidean coordinates of all the foreground pixels in the image, with an origin normally taken in one of the corners so that all coordinates have positive elements.

Figure 4.1 Binary Image

2.5. GRAY-SCALE IMAGE

For a gray-scale image, the intensity value is taken to represent height above a base plane, so that the gray-scale image represents a surface in three-dimensional Euclidean space. Then the set of coordinates associated with this image surface is simply the set of three-dimensional Euclidean coordinates of all the points within this surface and also all points below the surface, down to the base plane. Note that even when we are only considering points with integer coordinates, this is a lot of

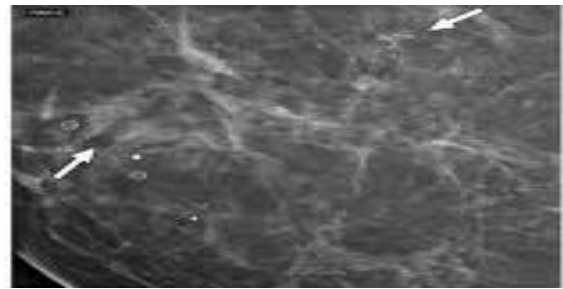points, so usually algorithms are employed that do not need to consider all the points.

Figure 4.2 Gray-Scale Image

2.6. IMAGE SEGMENTATION

For reasons such as; characteristics of breast tissue varies in texture and small size Micro calcification their detection and isolation of tissue still remains difficult. Select appropriate threshold is a sensible step, as a too high threshold can neglect the MCs which present less contrast, while a too low threshold makes that brilliant points which are selected do not correspond to some micro calcification these points are caused by the oscillations in the grey levels of the background, due to the noise which contaminates the image.
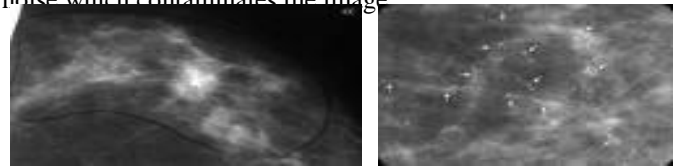

Figure 4.3 Segmented Image

2.7. K-MEANS ALGORITHM

K-means algorithm is a simple but elegant segmentation method. The main advantage of K-means algorithm is its simplicity. Speed of execution is very high. But the problem with K-means algorithm is that if the initial cluster centers are chosen incorrectly this algorithm may not converge. This happens in the case of noisy image mostly.K-Means algorithm is an unsupervised clustering algorithm that classifies the input data points into multiple classes based on their inherent distance from each other. The algorithm assumes that the data features form a vector space and tries to find natural clustering in them.

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2$$

The K-means algorithm is an iterative technique that is used to partition an image into K clusters. In statistics and machine learning also used, K-means clustering is the one of the most method of cluster analysis which aims to partition n

observations into k clusters in which each observation belongs to the cluster with the nearest mean. The basic algorithm is: Pick K-means cluster centers, either by chance or based on some heuristic.

We have proposed an adaptive K-means segmentation method for detection of micro calcifications in digital mammograms. In the present work, we have made an attempt to improve the performance of existing K-means approach by varying various values of certain parameters discussed in the algorithm.

3. SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

The classification of Micro calcification is one of the difficult tasks encountered in computer aided diagnostic systems. The effectiveness of the extracted features in classifying benignancy and malignancy of micro calcifications is not accuracy. Most of the previous method concentrates only on topological features for which two benign cases and two malignant cases are misclassified.
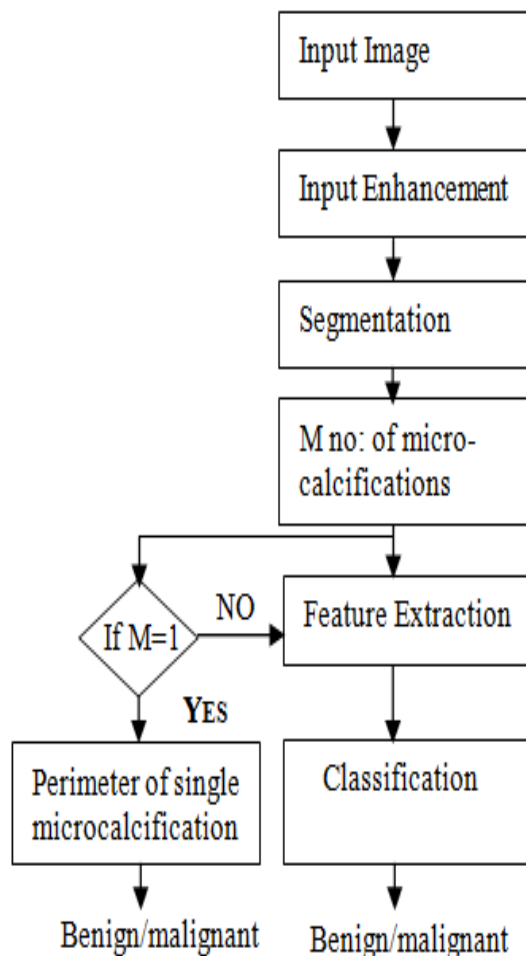

Figure 3.1 Existing System

Since shape features are also considered the problem of single node detection in previous work. Also the major problem of previous works is extracted at a single scale. The introduction of mammographic screening is not possible because of expense the relatively low incidence of breast cancer and low age of diagnosis.

In this figure 3.1 shows the system model to find the stage of the disease. The data used in the experiments consists of two datasets. The first dataset was extracted from the MIAS database, containing mage patches with the same size of 256*256 pixels. The second dataset was taken from the digital database for screening mammography database containing image patches.
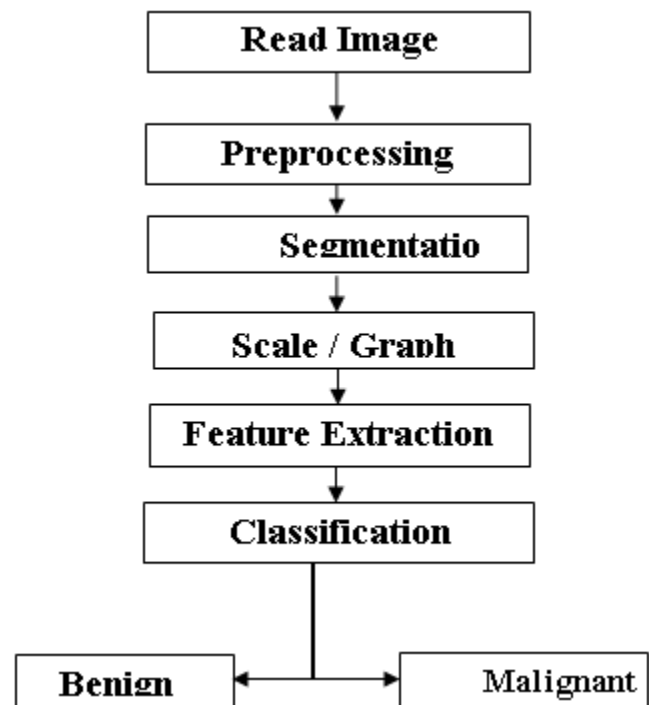
3.2 PROPOSED SYSTEM

Figure 3.2 Proposed System

The connectivity between the individual micro calcification is estimated by performing morphological dilation at multiple scales. The scale corresponds to the radius of the structuring element measured in pixels. As the scale increases dilation absorbs nearby pixels into individual micro calcifications. Therefore the connectivity between micro calcifications within the cluster is varied by the multiscale dilation. As the scale increases the connectivity will be higher for dense distribution and it will be lower for the wide distribution. Based on the connectivity relationship between micro calcifications within a cluster a micro calcification graph is generated. In a micro calcification graph, each node serve as an individual micro calcification, and an edge is connected between the nodes if the

micro calcifications are connected. The connectivity of the micro calcification cluster increases from small to large scales and the corresponding micro calcification graph becomes denser and denser and more edges are created in the graph.

Since the benign micro calcification cluster is less connected than malignant cluster the average vertex degree values of the benign cluster are smaller than those of the malignant cluster over the entire range of scales.

5. CONCLUSION&FUTURE ENHANCEMENT

5.1. CONCLUSION

A variety of research has been occurred on mammography. There are lot of various techniques that are used for classification of micro calcifications in mammogram images. Each of these techniques has their own specific contribution and limitations. In order to solve the various problems that occur in these techniques a system can be proposed which solves these problems. The project presented that a micro calcification on mammograms using graph method with supervised K-means with artificial neural network to detect disease stage such as Benign and Malignant micro calcification. In order to improve the system performance, the classifier has trained with the features of principal components. The simulated system provided that the better classification accuracy of input samples and compatibility in this diagnosis.

5.2. FUTURE ENHANCEMENT

A computer system devised that support aradiologist in small field of digital mammography has been proposed. As noted earlier, MCCs has very small and ubiquitous nature. So, we focused on the detection of clusters of micro calcifications. Result shows that watershed segmentation is more accurate than adaptive thresholding but more time consuming. Their results show that the system introduces an improvement in the breast cancer detection. In our future research, we would like to evaluate the proposed method on more mammograms from clinical images and other database. We would also like to extend this research for detect and classification of other factors of breast cancer such as mass.

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