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Visual up Gradation of Mammogram Image Using Grey Scale Extending Techniques

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Abstract-Breast cancer is the most common of all cancers affecting women in the developed countries. More middle-age women die of breast cancer than of any other single cause. This paper gives the idea about the Early Detection of Breast Cancer with some preprocessing steps. Grey scale Extending is basically improving the Interpretability or perception of information in an image for human viewers and providing better input for other automated image processing techniques. The principal objective of gray scale extending of a Mammogram Image is to modify the image to make it more suitable for finding the tumor cell location in the Breast. In grey scales extending Where Considerable background noise or variation in contrast and illumination exists, Local thresholding technique is more suitable than that of Global one. In this paper we are discussed about Local and Global thresholding to improve the visual up gradation of a Mammogram Image and Java as an image processing tool was used. With this technique we conclude that the proposed method is will performs more effectively for visual up gradation of mammogram image for further image processing steps . After further image processing steps like Triangulation we can find the location of different contracts cells in an image. This giving extra aid to radiologists to detect and classify the mammograms of breast cancer.

Keywords: Mammogram Image, Breast cancer, Cancer detection, Medical Imaging, Grey Scale Extending Algorithm.

I. INTRODUCTION

Mammography is in this case the best diagnostic technique for screening. However, the interpretation of mammograms is not easy because of small differences in densities of different tissues within the image. This is especially true for dense breasts. The aim of our work is tumor identification in mammogram images by using intermediate process in image processing algorithm of Grey Scale Extending Algorithm. Mammogram tumor classification is a leading area of research and to provide an algorithm that guarantees the presence of a tumor by combining several procedures to provide a foolproof method of tumor detection in a mammogram. In the fast several years cancer has been one of the biggest threats to human life; it is expected to become the leading cause of death over the next few decades. Based on statistics from the World Health Organization (WHO), cancer accounted for 13% of all deaths in the world in 2004; deaths caused by cancer are expected to increase in the future, with an estimated 12 million people dying from cancer in 2030 [2]. Of all the known cancers, breast cancer is a major concern among women. It is the second-most common and leading cause of cancer deaths among women [3]. According to published statistics, breast cancer has become a major health problem in both developed and developing countries over the past 50 years, and its incidence has increased in recent years. In the United States, in 2007, there were an estimated 178,480 new cases of breast cancer diagnosed and 40,460 deaths from this disease among women [4].

A tumor is an abnormal growth of cells in the human body. Tumors can be classified as either benign, which is non-cancerous, or malignant, which is cancerous. Benign tumors generally have well-rounded edges, are almost perfectly circular and do not have the tendency to spread. By utilizing the algorithm proposed in this paper, the objective is to successfully identify the presence of a tumor. In general Mammogram Image has missed type of pixels with different intensity value. After Segmenting the image by R*R variance thresholding Method, Each box with different Intensity value of pixels is extended with Local thresholding Method. In this classification is carried out with a separation of intensity value is called threshold [5]. Like other Image processing technique if the intensity value is low we cannot say that background because the cancer cell will have different intensity than the normal cell. So to get the solution for cancer cell findings we have to enhance the image with respect to both foreground and background with in the box of diffrent intensity value pixels. Local and Global thresholding technique will estimate different threshold for each pixel according to the intensities of pixel with in a window and with a whole Image pixels [6]. Early detection plays a significant role in the fatality of breast cancer. Technologies that aid in the early detection of cancers have therefore attracted much attention from the research community.

The Grey scale Extending of a mammogram Image intermediate step for Image up gradation in Mammogram Image processing step finding the cancer cell location. In this we have discussed Local thresholding which is useful only extending the images without ghost removal .If we are

in need to remove the ghost object from the image we have to use Global thresholding Method [7]. Breast cancer is the most common type of cancer in women, while the mortality rate of breast cancer of females over 40 years old is extremely high. If detected early, it can be treated early, and the mortality rate of breast cancer can be reduced. Therefore, the image processing technologies has been adapted to automatically breast images, select suspicious regions, and provide alerts to assist in doctors' diagnosis, reduce misdiagnosis rates due to fatigue of doctors, and improve diagnostic accuracy. In order to assist physicians in clinical diagnosis, a breast cancer detection algorithm was designed in this paper through Grey Scale Extending Algorithm.

II. EXPERIMENTAL PROCEDURE

Preprocessing

The input Image is segmented from the background which ensures the removal of noise, the whole image is divided blocks and grey scale variance is calculated for each block in the image is the compared with the threshold value, then it is deleted from the original image .This process is carried out for the whole mammogram Image.

This results show that the foreground regions segmented gives the breast structures and regions are not incorrectly segmented. The grey scale variance for a block of size R*R is defined

$$Z_{(k)=} \frac{1}{R^2} \sum_{i=0}^{R-1} \sum_{j=0}^{R-1} ((x(i,j)-y(k)) \quad (1)$$

$$y(k)= \frac{1}{R^2} \sum_{i=0}^{R-1} \sum_{j=0}^{R-1} (x(i,j) \quad (2)$$

If the variance is less than the global threshold, then the block is assigned to be a background region; otherwise, it is assigned to be part of the foreground.

Where Z(k) is the variance for the block k , x(i,j) is gray level value at pixel (i,j) and y(k) is the mean grey level value for the block .

Post Processing

Grey Scale Extending Algorithm

After preprocessing, Mammogram image is extended by intensity variance. This will be done by post processing step of Mammogram Image processing to find the Cancer cell location in Breast. The Global thresholding techniques are used when the background is uniform. But in cases where different parts of a document have different backgrounds or foregrounds vary in darkness, local thresholding methods can be very useful.

The Bersen's local thresholding

The Bersen's local thresholding method is a widely used local thresholding method[8]. The Local Threshold value of each pixel (x,y) is calculated by the relation if the window is centered at the pixel(x,y) the threshold for I(x,y) is defined by

$$T(x, y) = [Z_{(max)} + Z_{(Min)}]/2 \quad (1)$$

Where $Z_{(max)}$ and $Z_{(min)}$ are Maximum and Minimum Intensity level in a R*R window centered at (x,y) respectively. This threshold works properly only when the contrast is large .The contrast is defined as, if the contrast is less that a specific value k the pixel within the window may set to background or to foreground according to the class [7]. This blog entry is about java implementation of this method. This Method can achieve good results even on severely degraded process, but it is slow since the computation of local mean, max and min from the local neighborhood is to be done for each block of image pixels. Above threshold value calculation is without ghost removal. If the contrast is greater that a specific value k Global thresholding Method is used [8], [9].

$$T(x,y) = \begin{cases} Z_{(max)}+Z_{(min)}]/2 & \text{if } Z_{(max)}.Z_{(min)}>k \\ GT & \text{If } Z_{(max)}-Z_{(min)} \leq k \end{cases} \quad (2)$$

Where k is a contrast threshold. Threshold the image according to the thresholding curved surface T(x,y).If the intensity difference is greater than the threshold means local thresholding method is applicable else Global Thresholding techniques is useful to extend the image.GT is Global threshold value calculated when the contrast is lesser than the threshold k we are moving in to global threshold method[10]. In this paper we have implemented the technique of Otsu to the entire Image.

Otsu's method:

Otsu's method we exhaustively search for the threshold that minimizes the intra class variance (the variance with in the class), defined as a weighted sum of variance of the two classes:

For every possible t form 1 to maximum intensity:

Calculate within group variance:

Separate the pixel in to two clusters according to the threshold

1. Probability of being in group 1; probability of being in group2
2. Determine mean of group 1; determine mean of group 2
3. Calculate variance for group 1; calculate variance for group 2
4. Calculate weighted sum of group variance

Remember which t gave rise to minimum.

$$q_1(t) = \sum_{i=0}^{t} p(i) \quad (3)$$

$$q_2(t) = \sum_{i=t+1}^{Max} p(i) \quad (4)$$

Where $q_1(t),q_2(t)$ probability of each group and p(i) is the class probability; the total number of pixels in the image divided by the pixels in the class.

$$p(i) = n_i/N. \quad (5)$$

Class mean is calculated as

$$\mu_1(t) = \sum_{i=0}^{t} i\, p(i)/q_1(t) \quad (6)$$

$$\mu_2(t) = \sum_{i=t+1}^{Max} i\, p(i)/q_2(t) \quad (7)$$

The Variance of Individual group is

$$\sigma_1^2(t) = \sum_{i=0}^{t} [i-\mu_1(t)]^2\, p(i)/q_1(t) \quad (8)$$

$$\sigma_1^2(t) = \sum_{i=t+1}^{Max} [i-\mu_2(t)]^2\, p(i)/q_2(t) \quad (9)$$

The weighted sum of group variance

$$\sigma_w^2(t) = q_1(t)\,\sigma_1^2(t) + q_2(t)\,\sigma_2^2(t) \quad (10)$$

Threshold t is chosen, so that the between class variance σ_w^2 is maximized that is

$$t = \underset{0 \le t \le max}{Max} \left\{ \sigma_w^2(t) \right\} \quad (11)$$

We take the threshold that produced minimum intra class variance as a global threshold. In Otsu method extension of Multi threshold is possible.

III. RESULTS AND DISCUSSION

The Local Thresholding Method is sufficient for document images with slowly varying uniform background. However in Mammogram image, the backgrounds have taken as objects, so it causes great difficulty to ensure recognition of image for further image processing steps. So in our research we have discussed both the thresholding method according the contrast threshold Local thresholding works properly only when the contrast is large. If the contrast is less that a specific value k the pixel within the window may be set to be background or to foreground according to the class most suitably describes the window. This algorithm is depending on k value and also the size n of window R by R .Global thresholding method uses single threshold for whole image. When the intensity difference is less than the contrast threshold k. For Mammogram Image post processing step to find the cancer cell location we have used both Global and Local Thresholding for extending the Grey Scale to get clear viewer up gradation.

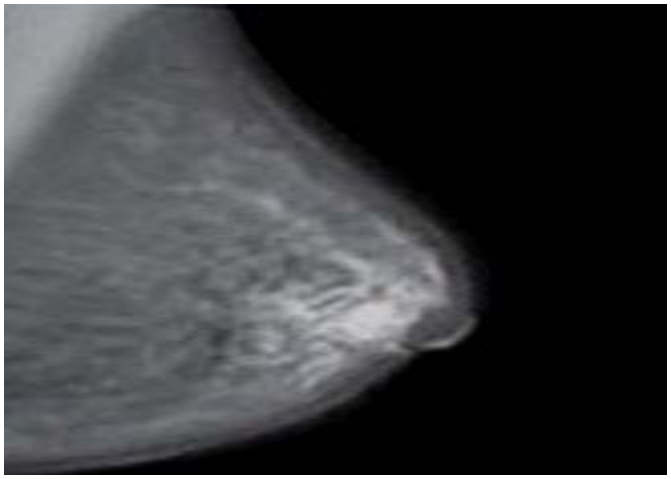

Figure.1: Input Image with Spread Cancer Cells

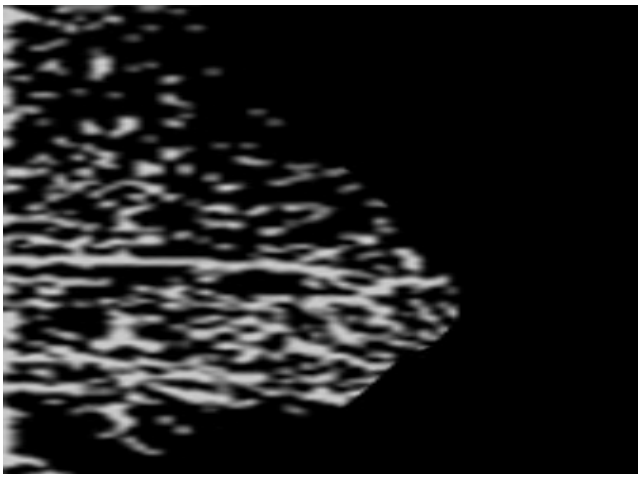

Figure.2: Mammogram Image after Segmentation

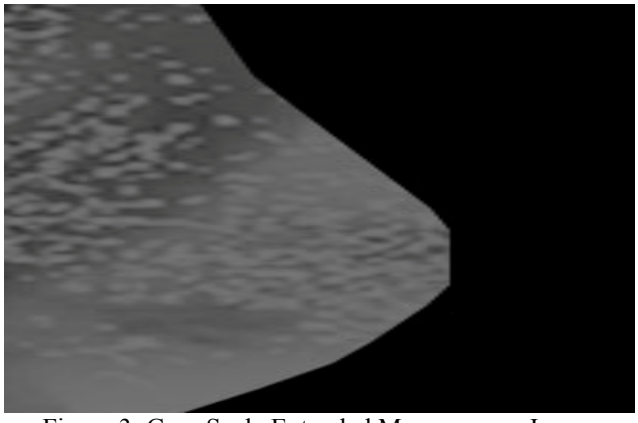

Figure.3: Grey Scale Extended Mammogram Image

IV. CONCLUSION

Earliest works in the field date back to the early 90s [8]–[10] but are in relatively small number, presumably due to the limited penetration of digital equipment in pathology. We thanks to recent advances in digital pathology, numerous cancer detection and grading applications have been proposed, including breast [11]–[20].

This paper presents a new way of Mammogram Image extending for automated detection of cancer cells image processing techniques. Local thresholding value is

determined by using contrast pixel value within a Local window size. According to the image up gradation for better diagnosis of cancer cells in breast the proposed methodology is applied over the whole Image. This algorithm suggested that improved performance can only be obtained combining the both thresholding techniques in a Mammogram segmented Image. So this gives the idea about the Early Detection of Breast Cancer preprocessing steps to get better image for analysis of breast cancer. This step is the preprocessing step to get clear points about background and fore ground according to contrast of pixels. If we get clear view points of an image it will be very useful for post processing steps like distance calculation between the points to get growth of cancer cell compare to normal cell. These algorithms modify images to achieve visually acceptable images by contrast enhancement. The purpose of this algorithm is to provide a useful advice to the end user, not give a final decision concerning presence of cancerous changes in an image .Algorithms helps as to improve a breast cancer detection system by preprocessing and cancer detection by proper data visualization. For further post processing step to identify the cancer cell area this algorithms gives clear visual to the human eye for diagnoses cancer at early stage, a better prognosis inducing a significant decrease in mortality. Moreover, the border of the image containing the tumor is cleared and the tumor is segmented by contrast stretching in the original image.

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