Evaluation of SUSAN Filter for the Identification of Micro Calcification

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ABSTRACT
Nowadays breast cancer is one of the major causes of death among women. This shows an early diagnostic techniques is critical for women's quality of life. Mammography is the main test used for screening and early diagnosis of breast cancer. Since micro calcifications are space-occupying lesions, described by their shapes, margins etc several image processing based techniques have been developed to improve the detection of primary signatures of this disease to increase radiologist's diagnostic performance. This paper presents an image processing based technique used for cancerous tumor mass segmentation. The processing techniques include enhancing the quality of the image, reducing the noise using filtering technique, segmenting the cancerous regions using SUSAN edge detection algorithm. The method was tested on 375 mammography images and achieved a sensitivity of 89%.

General Terms
Pattern Recognition, Image Processing, Computer Vision.

Keywords
Mammography, DWT, SUSAN filters, Circular Mask, Contrast Stretching, Segmentation**.**

1. INTRODUCTION
Breast tumors and masses usually appear in the form of dense regions in mammograms. A typical benign mass has a round, smooth and well circumscribed boundary; on the other hand, a malignant tumor usually has a speculated, rough and blurry boundary [1]. Early cancer detection becomes a crucial matter when the recent medical achievement can cure more than 80% of all stage one cancers [2].

In real life, doctors and radiologists have limited time to deal with a huge load of work. Human errors and mistakes can take place and cause wrong diagnosis when reading blur or low quality film/image of the patient. Computer-Aid is a solution for fast and accurate diagnosis. Several research work have tried to develop Computer Aided Diagnosis (CAD) tools [3]. They could help the radiologists in the interpretation of the mammograms and could be useful for an accurate diagnosis. The ultimate goal of CAD is to indicate cancerous locations with great accuracy and reliability. Thus far, most studies support that CAD technology has a positive impact on early breast cancer detection [4, 5].

The SUSAN edge finder presented in this work was implemented using circular masks to give isotropic responses rather than the traditional square masks [6]. The basic idea of SUSAN method is to associate to each pixel of the image a small circular area of neighbor pixels with similar brightness to the central pixel. The experimental result shows that this algorithm was more robust to noise and was rich in feature content and accurate.

The rest of this paper is organized as follows. Section 2, gives a brief overview of the related works. Section 3, give a brief description about the SUSAN edge detection algorithm. The proposed system is discussed in section 4. Conclusion and future enhancements were given in section 5.

2. RELATED WORK
There is extensive literature on the development and evaluation of CAD systems in mammography. Most of the proposed system follows a hierarchical approach. Initially the CAD system pre screens a mammogram to detect suspicious regions in the breast parenchyma that serve as candidate location for further analysis [7, 8]. In this the first stage is an algorithm of Gaussian smoothing filter, top hat operation for image enhancement in which the combined operations are applied to the original gray tone image and the higher sensitive lesion site selection of the enhanced images is observed. Then the second stage develops a thresholding method for segmenting tumor area [9, 10].

3. SUSAN FILTER
The edge detection algorithm described here follows the usual method of taking an image and, using a predetermined window centered on each pixel in the image, applying a locally acting set of rules to give an edge response. This response is then processed to give as the output a set of edges [6].

The SUSAN edge finder has been implemented using circular masks to give isotropic responses. Digital approximations to circles have been used with Gaussian weighting. The usual radius is 3.4 pixels which gives a mask of 37 pixels. The mask is placed at each point in the image and, for each point, the brightness of each pixel within the mask is compared with that of the nucleus (the centre point). Originally a simple equation determines this comparison:

$$c(\vec{r},\vec{r}_0)=\begin{cases}1 & if \quad |I(\vec{r})-I(\vec{r}_0)|\le t\\ 0 & if \quad |I(\vec{r})-I(\vec{r}_0)|> t\end{cases} \qquad (1)$$

where $\vec{r}_0$ is the position of the nucleus in the two dimensional image, $\vec{r}$ is the position of any other point within the mask, and $I(\vec{r})$ is the brightness of any pixel, t , is the brightness difference threshold and **c** is the output of the comparison. This comparison is done for each pixel within the mask, and a running total, **n**, of the outputs (**c**) is made as:

$$n(\vec{r}_0) = \sum_{\vec{r}} c(\vec{r}, \vec{r}_0) \tag{2}$$

This total **n** is just the number of pixels in the USAN, i.e. it gives the USAN's area. As described earlier this total is eventually minimized. The parameter **t** determines the minimum contrast of features which will be detected and also the maximum amount of noise which will be ignored.

Next, n is compared with a fixed threshold **g** (the geometric threshold') which is set to $3n_{max}$ / 4. Where n_{max} is the maximum value which n can take. The initial edge response is then created by using the following rule:

$$R(\vec{r}_0) = \begin{cases} g - n(\vec{r}_0) & if \quad n(\vec{r}_0) < g \\ 0 & otherwise \end{cases} \tag{3}$$

where $R(\vec{r}_0)$ is the initial edge response. This is clearly a simple formulation of the SUSAN principle, i.e., the smaller the USAN area, the larger the edge response. When non-maximum suppression has been performed the edge enhancement is complete.

The algorithm described above gives quite good result, but a much more stable and sensible equation to use for c in place of equation (1) is given below:

$$c(\vec{r}, \vec{r}_0) = e^{-\left(\frac{I(\vec{r}) - I(\vec{r}_0)}{t}\right)^2} \tag{4}$$

This form of Equation (4) was chosen to give a smoother version of Equation (1). This allows a pixel's brightness to vary slightly without having too large an effect on c, even if it is near the threshold position. This form gives a balance between good stability about the threshold and the function originally required to count pixels that have similar brightness to the nucleus as in the unvalued surface and to count pixels with dissimilar brightness as out of the surface.

4. PROPOSED SYSTEM

The various steps involved in the process can be explained in brief with the help of a block diagram as shown in figure 1.The input to the system is X-ray Mammography which is a special case of CT- Scan which adopts X-ray method to get the X-ray images of the breast known as Mammograms [2]. Mammography uses the high resolution film so that it can detect well the tumors in the breast. Low radiation is the strength of this method. Mammography is especially used only in breast tumor detection.

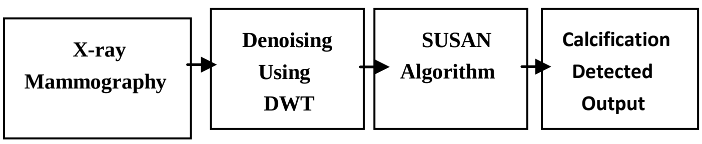

Fig 1: Proposed System.

4.1 Enhancing the Contrast and Quality of the Image

Normally, the image's histogram is dense in one side of the spectrum as shown in Figure 4. This will cause the image to be very dark or very bright, different parts of the image with different grey intensity will not be well detected by eyes. Spreading out the spectrum of the histogram (Figure 5) will enhance the contrast of the image. Normal eyes can now detect the full scale of the grey intensity easily. The manipulated image (Figure 3) is clearer than the original image (Figure 2). In addition, the real boundary of the breast appears clearer, so the position of the cancer is detected more accurately. However, the noise appears on the black background. To solve this problem, we proceed to next stage which involves reducing noise.

4.2 Denoising Using Discrete Wavelet transform

The coefficients arising from noise are characterized by high frequency so most de-noising techniques are methods of low-pass filtering in which channels of higher frequencies are cut off while channels of lower ones are enhanced. A simple way of de-noising is thresholding where the wavelet coefficients whose magnitudes are below a given value – the threshold – are set to zero. Here the purpose is served by Discrete Wavelet Transform (DWT). DWT can be used to reduce the image size without losing much of the resolution [4]. For a given image, you can compute the DWT of, say each row, and discard all values in the DWT that are less than a certain threshold. We then save only those DWT coefficients that are above the threshold for each row, and when we need to reconstruct the original image, we simply pad each row with as many zeros as the number of discarded coefficients, and use the inverse DWT to reconstruct each row of the original image [5]. We can also analyze the image at different frequency bands, and reconstruct the original image by using only the coefficients that are of a particular band, the very same technique that we are using in cancer detection.

Fig 2: Input Image

Fig 3: Enhanced Image

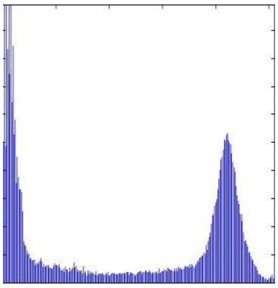

Fig 4: Original Histogram

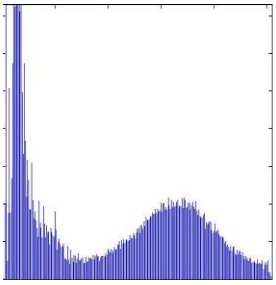

Fig 5: Equalized Histogram

We experimented with the different types of wavelets aiming at incrementing the percentage of energy that corresponds to the horizontal, vertical and diagonal details of the third level of wavelet transform. At last the Least Asymmetric Daubechies' wavelets were proven to be the most promising wavelets. This choice is preferable since the Least Asymmetric Daubechies' wavelets have finite length and are nearly symmetric. Due to these features, they can achieve high correlation with the clustered micro calcifications, and, therefore, they can effectively enhance micro calcifications as shown in figure 6.

Fig 6: Noise Reduced Image Using DWT

4.3 Identification of Micro-Calcification

The micro-calcifications have got specific intensity of brightness and also size. In this section we checks for these criteria's in the de-noised mammogram image using a special mask designed using Smallest Unvalued Segment Assimilating Nucleus (SUSAN) Filters and the concerned areas are extracted from the mammogram. The mask of SUSAN method is different from other convolution mask, which is a circular mask instead of a square mask. The basic idea of SUSAN method is to associate to each pixel of the image a small area of neighbor pixels with similar brightness to the centre pixel. This small area is called USAN (Univalue Segment Assimilating Nucleus). The mask is placed at each point in the image and, for each point; the brightness of each pixel within the mask is compared with that of the nucleus (the centre point). Each point in the input image is used as the nucleus of a small circular mask, and the associated USAN is found. The USAN area falls as an edge is approached (reaching a minimum at the exact position of the edge), and near corners it falls further, giving local minima in USAN area at the exact positions of image corners. The algorithm, in brief performs the following steps:

1. Place a circular mask around each pixel in the given image.
2. Using equation (4) calculate the number of pixels within the circular mask which have similar brightness to the nucleus.
3. Using equation (3) subtract the USAN size from the geometric threshold to produce an edge strength image.
4. Apply thinning operation to the above obtained result to get the cancerous regions segmented out.

4.4 Reversing Color and Showing Cancerous Areas in the Original Image

After thresholding the high risk areas, it should be embedded on the image in order that the doctor can know the position of the cancer. This is achieved using image multiplication since two multiplied images must have the same class and size. In logical (binary) image black color is coded as 0 and white color is coded as 1. Hence, we need to change or reverse the color of the segmented image in order that the black background does not neutralize the whole image after multiplication. Figure 7 shows the output of the segmented image and figure 8 shows the segmented cancerous areas embedded in the original image.

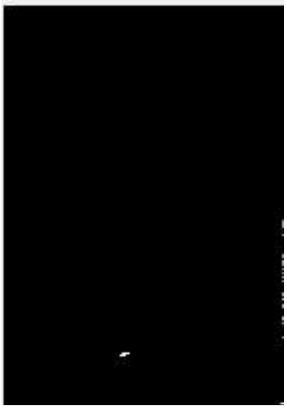

Fig 7: Segmented image

Fig 7: Resultant Image

5. CONCLUSION AND FUTURE ENHANCEMENTS

This work proposes a Computer Aided Diagnosis (CAD) technique to detect the cancerous areas in the X-Ray image of breast with great degree of accuracy. It even detects cancerous regions that are not detectable by a breast self exam or a typical clinical breast exam at the very early stages of cancer. Thus enhances early detection in a great magnitude.

The experimental results indicate that the performance of the SUSAN algorithm in the presence of noise is also good since it uses no image derivatives. The integrating effect together with its non-linear response, give strong noise rejection in the final output. Although the final image still shows some of non-cancerous areas; on the consultation with doctors, this work was considered to be a very useful aid for them to read the image more accurately and it saves their time.

6. REFERENCES

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