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# **Breast Cancer Detection by Kirsch Algorithm**

Hardik Anil Patil, Akash Rajendra Patil, Sanket Sanjay Mhatre

4th Year Engineering Student, Dept. of Computer Engineering, VESIT, Mumbai University, India

4th Year Engineering Student, Dept. of Computer Engineering, VESIT, Mumbai University, India

4th Year Engineering Student, Dept. of Computer Engineering, VESIT, Mumbai University, India

**ABSTRACT:** Edge detection is very important for processing of images. There are clustered microcalcifications in digitized mammograms. Edge detection is used for automatic analysis of these clustered microcalcifications in digitized mammograms with the help of computer aided diagnosis system. Edge detection will also identify and locate sharp edges of discontinuity in images. This paper aims at new method for clustered microcalcifications edge detection. Here we will talk about what Kirsch edge operator and edge linking with Markov model and how it will help in microcalcifications edge detection. First initial edges and then thin initial edges will be extracted by Kirsch edge operator since it is used as derivative mask. It will fill many gaps in edge image using edge linking technique.

**KEYWORDS**: Edge detection, Kirsch compass kernel, Edge linking, Threshold.

#### I. INTRODUCTION

Breast cancer can be detected earlier with the help of significant radiological signs by presence and appearance of microcalcifications [1]. Computer- aided diagnosis (CAD) schemes have been developed by many investigators for identifying regions of probable micro calcification clusters in mammograms [2]. Edge extraction of micro calcification clusters has a great importance in computer-aided diagnosis system for the instinctive detection of clustered micro calcifications in digitized mammograms [3]. edge detection is an elemental tool for image segmentation [4]. Kirsch compass mask is a most commonly used mask which is used for finding edges. It is a very unique mask when compared to other masks. It is having the advantage of changing mask according to our own requirements [4]. Firstly take profit of Kirsch operator to extract initial edges of micro calcification clusters [4]. In order to obtain closed boundaries and micro calcifications we fill gaps which exists in initial edge images of micro calcifications using edge lining technique [6]. Lastly, we eliminate the edges of background tissue and noise using Markov model [7]. For mammograms, thresholding usually involves selecting a single gray level value from an analysis of the grey-level histogram, to segment the histogram into background and breast tissues. All the pixels with grey level value less than the threshold are marked as background and the rest as breast. Thresholding uses only grey level value and no spatial information is considered. Therefore, the major shortcoming of the threshold is that there is often an overlap between grey levels of the objects in the breast and the background. Micro calcification clusters are the primary indicator of malignant type of breast cancer, the detection is important to prevent and treat the disease. The micro calcification appears in small clusters of a few pixels with relatively high intensity and closed contours compared with their neighboring pixels. However, it is a challenge to detect all the micro calcifications since they appear as spots which are slightly brighter than their background. The microcalcifications in mammograms can be detected by using dual threshold method [5]. Experimental results showed that proposed method can locate the micro calcifications exactly in the mammograms as well as restrain the contours produced by the noises. Mammography is the process of using lowenergy-X-rays (usually around 30 kVp) to examine the human breast and is used as a diagnostic and a screening tool. The goal of mammography is the early detection of breast cancer, typically through detection of characteristic masses and/or microcalcification. A mammogram is an x-ray picture of the breast.

Microcalcifications discovered on a breast cancer screening mammogram are a means of detecting the cancer at an early stage, frequently as ductal carcinoma in situ. DCIS has an extremely high cure rate, generally over **95%**. So early detection with our method can be beneficial. **Breast calcifications** are common on mammograms, and they're especially prevalent after menopause. Although **breast calcifications** are usually noncancerous (benign), certain patterns of



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**calcifications** — such as tight clusters with irregular shapes — may indicate **breast** cancer or precancerous changes to **breast** tissue Mammography is the most effective method for the early detection of breast diseases. However, the typical diagnostic signs such as microcalcifications and masses are difficult to detect because mammograms are low-contrast and noisy images. Breast cancer continues to be a significant public health problem in the United States. Approximately, 182 000 new cases of breast cancer are diagnosed and 46 000 women die of breast cancer each year. Microcalcifications are first enhanced based on their brightness and nonuniformity. Then, the irrelevant breast structures are excluded by a curve detector. Finally, microcalcifications are located using an iterative threshold selection method. The shapes of microcalcifications are reconstructed and the isolated pixels are removed by employing the mathematical morphology technique .The major advantage of the proposed method is its ability to detect microcalcifications even in very dense breast mammograms. A series of clinical mammograms are employed to test the proposed algorithm and the performance is evaluated by the free-response receiver operating characteristic curve. The experiments aptly show that the microcalcifications can be accurately detected even in very dense mammograms using the proposed approach.

#### II. RELATED WORK

For the computer assisted detection of mass lesions in digital mammograms methods have already been issued. These methods can be classified as either pixel or region based. One of the method is Pixel based. In Pixel based method we will extract statistical features from each individual pixel in the mammogram image. In order to identify record pixels of interest these methods use a classification scheme. In some cases, a further examination could indicate if a mass represented by these pixels is good or harmful. Another method is region based and it searches whole areas of the mammogram image for masses. Researcher presents a hybrid method for computer assisted screening of mammograms for masses. The hybrid method is a combination of pixel and region based analysis.

#### **III. PROPOSED ALGORITHM**

We use a step, which thins the focus of analysis from every pixel in the image to groups of pixels, which are areas in the image. These image areas are screened to discover if they have possible masses. Those with possible masses are then extracted and processed. This processing includes multiscale tests to refine the suspicious areas. This approach offers the probable for enhanced efficiency and lowers the error for computer assisted screening of mammogram images [6]. The technique uses a form of template matching at multiple scales to locate pixels in the image, which may be part of a mass. The resulting image is adaptively to a predetermined level of accuracy and then the remaining pixels are grouped together and extracted. Imaging techniques play an crucial role in helping perform mammogram, especially of abnormal areas that cannot be felt but can be seen on a conventional mammogram or with ultrasound [7]. It develops a supporting tool to easy recognition of abnormal masses in mammography images, which will lower the false positive (FP), false negative (FN) detection. In this paper, we explore many methods of edge extraction and propose a novel approach for edge detection.

Maximum edge strength can be found in a few predetermined directions by using edge detection method proposed by Kirsch. The operator takes a single kernel mask and rotates in45 increments through all 0.8 compass directions (ie) N, S, E, W, NW, SW, NE, SE. The edge magnitude is calculated as the maximum magnitude across all directions [8]. Each and every pixel of images all use these 8 masking to make convolution, each masking has great response to a certain edge direction, the maximal value of all 8 directions is set to output value of this point. The masking sequence number of greatest response constitutes the code of edge direction. Assume, the original sub-image of  $3 \times 3$  is as following

$$\begin{bmatrix} a_{2} & a_{2} & a_{1} \\ a_{4} & (i, f) & a_{0} \\ a_{5} & a_{6} & a_{7} \end{bmatrix}$$



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Kirsch Compass Mask is also a derivative mask which is used for finding edges. This is also like Robinson compass find edges in all the eight directions of a compass. The only difference between Robinson and kirsch compass masks is that in Kirsch we have a standard mask but in Kirsch we change the mask according to our own requirements. With the help of Kirsch Compass Masks we can find edges in the following eight directions.

- North
- North West
- West
- South West
- South
- South East
- East
- North East

We take a standard mask which follows all the properties of a derivative mask and then rotate it to find the edges.



### NORTH DIRECTION MASK

| -3 | -3 | 5 |
|----|----|---|
| -3 | 0  | 5 |
| -3 | -3 | 5 |



After the edges are extracted, the precursory templates are multiplied by 3x3 region of the image and choose the template of highest output value. After that take this maximal value as the edge intensity of central pixel point, take the maximal value template Mk's direction k (k 's value is illustrated as Figure 9 1) as its edge direction. Supposed a point



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P(j, i) in a image and its grayscale values of eight neighborhood unions are shown as Figure (2) and set qk(k=0,1,...7) as edge intensity of the k th direction when a image is dealt with by the k th template of Kirsch operator, then the edge intensity of P (i, j) is S(i, j) maxq (k k =0,1,...7) and the corresponding edge direction D(i, j)={k/qkis maximum} Kirsch algorithm is based on step edge, according to the attributes of images themselves and value-taking conditions of Kirsch values, it can adjust threshold values to obtain most possible edge point of images, so it can completely be removed from artificial participation. When the contrast between the foreground and background is very savage and centralized. Kirsch algorithm will have very efficient performance and it can adjust threshold values to obtain most Possible edge point of images, so it can completely be removed from artificial participation. Variables concerned in the selection of an edge detection operator consists of edge orientation, edge structure and noise environment. Therefore in order to look for vertical, horizontal ,diagonal edges operators are optimized.. Techniques used on noisy images are typically larger in scope and the method wants to be chosen to be receptive to such a regular change in those cases. Hence the aim is to do the analogy of a variety of directions and analyze the performance.

#### IV. NOISE REMOVAL

The presence of noise in the initial edge image, however, imposes a necessity for noise elimination. For each edge point in the initial edge image, the three-by-three neighborhood centered on that point is examined, if the total edge point number is more than two, then, these edge points will be reserved, otherwise, all edge points in that neighborhood are taken as noise [9]. In order to obtain single pixel edge, the removed noise edge image need to be thinned, the thinning method is described as follows. Foremost, we define sixteen kinds of edge modes and corresponding pattern codes [10, 11]. Secondly, we examine each point in the edge image, For each edge point, ( i, j) the three-by-three neighborhood EBij centered on that point is examined, if the total edge point number in the neighborhood EB is more than 3, then, we obtain a three-by-three neighborhood EBij corresponding to EBij in the filter image FI. Major profits of this technique include efficient flexibility and excellent performance. Its limitations are: clear background-foreground relation requirement and pixel-precision.

The scenario consists of the following steps:

**Extraction**- in the initial step one of the Image Thresholding techniques is applied to gain a region corresponding to the objects (or single object) being inspected.

**Refinement**- the extracted region is often affected by noise of various kind (e.g. due to inconsistent lightning or poor image quality). In the Refinement step the region is developed using region transformation techniques.

**Analysis**- in the last step the refined region is subject to measurements and the final results are computed. If the region represents many objects, it is split into individual blobs each of which is investigated separately.

#### V. SIMULATION RESULTS

Many experiments were carried out on different ROI with micro calcification clusters to test the performance of our algorithm. The same as other previous works, the quality of edge idebtification results is evaluated subjectively. Canny's edge detector is a well known edge operator. It is always among the best performers in various edge operation evaluation experiments and has become part of the standard against which the performance of a newly developed edge detector is compared. We compare the result of our algorithm with one of Canny's edge detector to show the better performance.

Figure is a part of experiment results

1)Original ROI with microcalcification clusters

2)Extracting results of canny operator

3)Extracting results of our algorithm for multiple edges

4)Extracting results of our algorithm for single image

Our algorithm can obtain closed boundary with less noise and background tissue edges for multiple images and single image





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INPUT IMAGE



RESULTS OF CANNY METHOD



OUR OUTPUT



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#### VI. CONCLUSION AND FUTURE WORK

In this paper, we propose a new edge detection algorithm of micro calcification clusters in digital mammograms based on kirsch operator and Markov model. The proposed approach was applied to boundary extraction of micro calcification clusters. We compared the extraction results with Canny operator. Our study showed that in terms of noise, over-detected points, closed boundary, our algorithm was better, compared to the Canny method. These results demonstrated that our method is an effective way to extract micro calcification clusters. Therefore, the proposed algorithm can be applied to characteristic extraction of micro calcification clusters. The key idea of the proposed method is to apply the fuzzified image to locate the ROI's and to interact with the original image to preserve the fidelity. The advantages of the proposed approach are: 1) The microcalcifications are accurately detected even in mammograms of very dense breasts. 2) The irrelevant breast-structures can be easily identified and removed. 3) The processing time is very fast since the major computation is for global thresholding. 4) Some parameters can be adjusted in order to find out different levels of TP and FP rates. It would facilitate the computer aided diagnosis. 5) The experimental results encourage the usage of the proposed approach for microcalcification detection and it provides a good platform for further processes such as categorizing the lesions into benign and malignant. Further improvement of the proposed approach can be achieved by using higher-resolution images , more powerful contrast enhancement algorithm , neural networks, etc.

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