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Boundary Detection to Segment the Pectoral Muscle from Digital Mammograms Images

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Abstract*: Breast cancer is class of cancer that sets off when the breast cells grow out of proportion and control. The radiologist recognizes the sign of breast cancer by performing a kind of X-ray called screening mammography. During analysis of mammography the biggest problem arise because of the presence of pectoral muscle. The mass of tissue on which the breast is rest called the Pectoral muscle. The primary problem is that pectoral muscle area density is almost similar to the tumour cell and this condition generates confusion to recognize the tumour cell. For analysis the Medio-Lateral oblique (MLO) views of mammograms is being taken so that the complete breast image can be viewed. Some part of the pectoral muscle also gets visible along with the breast in the MLO view which must be segmented from the mammogram. Pectoral muscle involvement can lead to false positive or false negatives. The workforce shortages of Radiologist with respect to growing demands and to declare the result in a very short time have also increased the pressure. Consequently, a radiologist is sometimes unable to detect an anomaly. This is the time where CAD system can help radiologists to detect breast cancer at an earlier stage. Numerous strategies for the selection of the pectoral muscle have been suggested and developed so far. This article reviews the different segmentation techniques for pectoral muscle removal in mammograms through digital images..

Keywords: Pectoral muscle, Mammography, Computer-aided diagnosis, Segmentation.

I. INTRODUCTION

Finding the precise breast profile segmentation of the female mammogram is a major challenge. In the mammograms low dose X-ray are being passes across the breast for finding the clear image of the breast so that cancer can be detected. An image of the smooth tissues, thick tissues, pectoral muscle, and fibro-glandular region is generated during this process. The Radiologist examined the cases through screening programme. Here the main role comes in the picture and that come through the expertise level and experience of the Radiologist. Any kind of changes in the mammogram which have been taken within a year or two may help to identify the cancer in the early stage before any symptom felt by the patient or doctor. [1][2].The probability of protecting women from breast cancer can be improved and also aggressive treatments can be avoided if any kind of changes in the breast is confirmed at its early stage of cancer. Modern mammography machines produce the high-quality digital images with low radiation doses of 0.4 mSv of X-ray which gives 2 views of each breast. Because of the sensitivity of the screening the double reading of mammography is also recommended [3]. The graph shows the age group between 30 to 40 where case of breast cancer are increasing (Figure 1) [82] and the number of new cases in 2018 which include both sexes with all ages (Figure 2) [4].

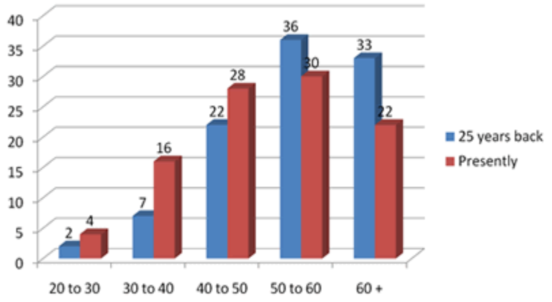

Fig. 1.New cases in 2018 ,both sexes,all ages

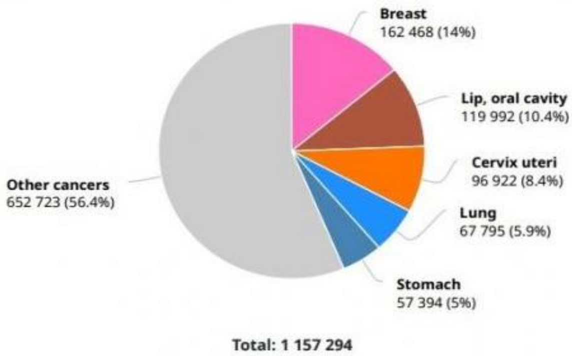

Fig. 2.New cases in 2018 ,both sexes,all ages

The Swedish Two-County Trial show that the women age between 40 to 74 year have gone through the screening through mammography and in the result it has been found that there is a reduction in breast cancer mortality of 30% [5].In the analysis the 320 Cancers found in a sample that has been taken between August 1985 and May 1990 and it has been identified that 77 cancers had been missed in Mammography [1]. The double interpretation gives better result in detecting cancer through screening mammograms approximately 6 to 15% compared to single interpretation reading.

Sensitivity plays very important role in screening mammography because it has the ability to detect the cancers. Another important factor is the breast tissue density which can affect the sensitivity of the screening as well as it also increases the risk of breast cancer [6] [7].The Double

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reading enhances the accuracy but at the same time it also increases the use of expert manpower. Because of capacity constraints and high intra-observer variability, the implementation is restricted [8].

A. CC and MLO views

The mammograms images have two standard orientations views during screening. The one is known as Craniocaudal (CC) views and another is known as Medial-lateral-oblique (MLO) views [1]. The whole breast parenchyma should be depicted in the Craniocaudal view. While the mammogram is being carried out, the fatty tissue visible near to the chest wall should look like a dark strip either on the top right or top left area and it is known as pectoral muscle. The MLO view should be taken in such a manner where the maximum part of the pectoral muscle can appear. To facilitate this, the MLO view has been drawn at 450 angles. Part of the pectoral muscles is also shown on the mammography using MLO view. In the (Figure 3) CC and MLO projection is shown which also represents the top-down view of the breast. The MLO (Figure 3) projection is important as it allows to portray most of the breast tissue because of this reason MLO views are always preferred.

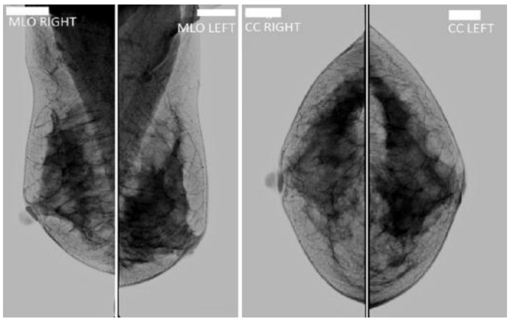

Fig. 3.Medial-lateral-oblique (MLO) and Craniocaudal (CC) Projection of the left & right breast

B. Radiologists are in Dire Shortage

The developed countries are also facing challenges and feeling pressure in the healthcare system because of the increasing cost in the treatment also the patient has to wait for long time. To overcome from all these issues there is a need a trained physician and care providers so that growing demands can be fulfilled in the short period of time but in today's scenario it is impossible to provide the solution. The only solution can be provided by involving technological breakthroughs. The report publishes on clinical radiology in UK which states that "increased workforce shortages and spiraling costs. The radiology workforce is showing signs of stress and burnout". The developing countries are also facing the shortage of the trained radiologists where the infrastructure is lags behind [9].

C. Utility of CAD in mammography

The utility of CAD arguably depended on the skill of the radiologist. By taking help of CAD the sensitivity of mammography can be improved .It also assist the radiologist to detect the suspicious area [10].The different issues can be sorted with the help of computerized mammography image analysis. The radiologist report regarding mammography can have errors and may be ascribed. The possible reason could be that radiologist not having good experience, lacking of perception, inadequate analysis of radiological abnormalities. So all these problems could be sorted out by taking help by computer analysis through medical image processing. The analysis of the digitalized images can be done by algorithms as second reviewer for the radiologist due to its consistency, reliability and speed. Analysis of mammography is time consuming as well as exhaustive process. Analyzing hundreds of mammograms every day can prove to be a very time taking and exhaustive process for radiologists. And as a result, it may produce the false positives or false negatives. Also, it is impractical to analyze hundreds of mammography images daily. Computer aided detection technique may prove to be useful in situations where the screening and analysis of large number of films are done and where due to the lack of attention or fatigue the perception of the radiologist may be reduced and vary [11]. Due to this reason a radiologist cannot detect an abnormality correctly at times. In breast CAD, accurate breast segmentation can be achieved if the noises present in the mammography can be removed. From the study it is clear that with the help of CAD the performance to detect cancer has been improved and around 5.2–10.6% more cancers has been detected .The quality have been improved when the two readers read the mammography image with CAD. The specificity was decreased slightly for the four readers with CAD (range 1.4%–5.7%) but in general there was improvement in the result to detect the cancer with the help of CAD [12].In CAD technology there is a need to provide the breast feature that can be quantified automatically so that the radiologists can provide the clinical evidences and further analysis can be done. During mammography CAD, the main aspect is adequate segmentation of the pectoral muscle border and the skin space border to analyze the contours of the breast. From the available literature the various techniques like thresholding, morphology-based technique, region-growing, texture-based and active contour have been provided. These techniques have emphasis on the accurate segmentation of the pectoral muscle [13].

D. Pectoral muscle presence in the Mammography and their impact

Pectoral muscle is a predominant area of density in maximum instances of mammograms, and due to pectoral muscle and breast parenchyma having a large degree of resemblance, that it can cause problems in assessment. This similarity may mislead the diagnosis of cancer. So that to overcome from the false positive or false negative result, which could be dangerous for the Human. That's why segmenting the pectoral muscle in a clear and concise way is still a challenging job. Apart from the problems discussed above the other issues is the wrong estimation of the density level which is included in the mammogram data. While taking help through the CAD for detecting the breast cancer there is a need of the pre-processing to remove the noises.

Removing noises from the images required certain steps. The process is known as pre-processing that too without losing any important anatomical information. This pre-processing step removes the different types of the noise (Fig.2) that appear in these mammogram

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images. The removal of these noises is required otherwise the presence of the noise may affect the analysis and result of the mammography. The various kinds of noise can be such as high-intensity tag, low-intensity label, scanning artifact, tape artifact, light leakage, screening system imperfections and low contrast along the breast skin [81].As per the data provided by the Poorolajal, Jalal, et al. the Relative risk [RR] is equivalent to 0.69;95 percent confidence interval is 0.56 ; 0.84 ; P, .0001) with the consensus information is (RR = 0.73 ; 95 percent confidence interval: 0.59 ; 0.84 ; P = .001) were significantly reduced in breast cancer mortality among females referred to screening on the basis of both local endpoint information.

The number of females was 414 according to local information and 519 according to consensus information who were required to undergo screening for 7 years at 29 years of follow-up to avoid one death from breast cancer. Most prevented fatalities from breast cancer would have happened after the first 10 years of follow-up (without screening) [5].To find out the breast cancer in early stages, it is suggested that females undergo a screening test, usually a mammogram, before patients show symptoms. Mammography involves exposing the breasts of a patient to low X-ray radiation concentrations. Due to the distinct X-ray absorption rates of typical as well as normal tissues, mammograms can recognize breast cancer. It is proposed that females follow the conventional procedure and go through a screening test usually through mammogram to discover breast cancer in early stages.

Tumors can appear as micro-calcifications masses, distortions or masses on mammograms [15] hence it may partly cover the dense tissues in patients with dense breast tissues, leading to masking impacts and making mammography less vulnerable. The pectoral muscle is a noticeable dominant region in MLO opinions in routine mammographic testing, lying either on the right or left top corner as shown in Figure 4. It is a thick region close to the chest that may influence the detection precision. Due to the high complexity of breast tissues or dense breast tissues, up to 30% of breast cancers may be missed by physician [16]. The pectoral muscle appears to be semi-elliptical along the breast wall in the CC view. Whereas in the upper corner of the mammogram, MLO view involves more region and its shape is approximately like a triangle with a right angle. The pectoral muscles which dominate the screening mammograms perspective of the MLO. The overlap creates more heterogeneous regions by mixing pectoral tissues with existing fibro-glandular breast tissues. The pectoral regions are often denser and have a greater contrast with the neighbouring tissues, thus breast parenchyma can be effectively segmented. In many situations, however, the pectorals are less contrast than the dense tissues that surround them, leading to weaker disparities in the border. There are also cases where the muscles have the same density and are attached to the fibro-glandular tissues as the adjacent breast parenchyma. Thus, automatic detection of lesion may cause hindrance in terms of false positive [17][18][19]. The pectoral muscle should always appear as a elevated intensity over the upper back boundary of the image with the triangular area if the MLO view is properly portrayed. It is important that in the MLO view the pectoral muscle must visible as a high-intensity triangular area across the upper posterior margin of the image. Only 30 percent to 40 percent of pictures show the pectoral muscle that is why Craniocaudal view (CC) is not regarded for the purpose of analysis. In many fields of mammographic analysis, pectoral muscle segmentation is useful [20].The region surrounding the pectoral muscle is a prevalent region for the development of cancers and is particularly monitored to decrease false negatives by radiologists. Segmentation of the pectoral muscle is therefore required before identification of lesions [19]. Similarly pectoral muscle segmentation is necessary for automatic analysis of breast tissue density. There are large differences in appearance between different types of parenchyma, partly due to variation in image acquisition [21] [22]. The pectoral edge is also used from distinct mammographic angles as one of the key point in 3-dimensional reconstructions [23] and is one of the main landmarks in mammography for analysis and for and comparison [24]. Furthermore, radiologists suggest that the pectoral muscle for a high-quality MLO mammogram be considered at or below the level of the nipple [25] [26]. Scientists also proposed convex pectoral margin [18].Deleting the right pectoral muscle will decrease the algorithm's error and computational load. Successful CAD techniques depend on the exact differentiation of the breast mass between pectoral muscles and tissues. The use of computerized mammographic assessment is regarded to create a crucial contribution to ease the growing workload and help in breast cancer detection. It is evident from the literature available that extraction of pectoral muscle is not a difficult but it is very complex and requires participation of an experienced radiologist to distinguish between the pectoral muscle and tissues because in maximum cases the breast tissues are not clear. In some situations, the pectoral muscle is also observed to be completely absent. This random variability in pectoral muscle position coupled with its resemblance to breast tissues in density makes segmentation a difficult task. As a result, many of the techniques discussed in the literature are not fully automatic [27] [28] [29] [79]. The Pectoral Margin is not, as others presume, a straight line [21], but it has a largely concave margin on the upper side of the nipple, concave or convective, or a mixture of the two for the lower part of the Margin. The variation of the margin between mammogram is so complicated that there is no single geometric or mathematical model available [14]. A lot of techniques have been suggested to fix this issue in the last few years. Approaches to straight line estimation refine the border with a gray intensity shift from a straight line [30] [31] [20] [32] [33]. These approaches need to be associated with other sophisticated techniques for the curved border of the pectoral muscle area. Increasing regional methods examine neighboring pixels of the original points and divide a mammogram into several areas [34][35][36][37][14].These methods do not always provide excellent efficiency in low-contrast mammograms, as less thresholds are not sufficient for segmentation[38][39][40][41][42][10][43]. Polynomial fitting of the seed points [44][45][80] is suggested to enhance the output for which the pectoral muscle was partly contrasting. These methods rely more on well-contrast border seed points, their segmentation findings are not stable in low-contrast areas [46]. Usually, current techniques used empirical thresholds to identify original pectoral muscle area boundaries.

E. Significance

In the mammographic image apart from the pectoral muscle there are various other parts which affect the decision process and reduce the detection accuracy. These sections include low and high intensity labels to be removed in the mammogram, scanning artifacts, etc. The removal of these noises is required otherwise the presence of the noise may affect the analysis and result of the mammography. Artifacts on mammograms reduce the image quality and may create clinical and technical difficulties for the mammographer. The distinct kinds of noise can be such as high intensity label, low intensity label, scanning artefact, tape artefact, light leakage, low breast skin contrast and imperfections in the scanning method. [14]. Removing noises from the images required certain steps. The method is also known as pre-processing, without any significant anatomical data being lost. This pre-processing step removes the different types of the noise (Fig.4) that appear in these mammogram images.

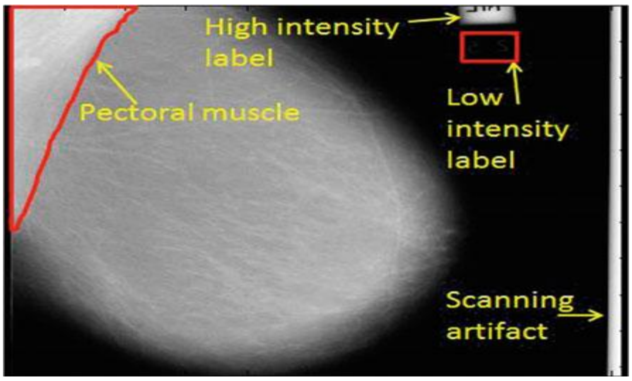


Fig. 4.MLO view mammographic Imag

II. BACKGROUND STUDY

A. Intensity Based Approach: This technique is based on the distinction between Pectoral muscle region’s and breast parenchyma because of the change in the intensity. A pectoral muscle area's intensity range is greater than that of neighbouring tissues. The increase and fall of pectoral muscle intensity provides useful data to better accurately separate the pectoral muscle. In the context of image processing, an image's histogram normally refers to a pixel intensity histogram. This histogram displays pixel intensity frequency values. The x axis picture histogram indicates the intensities of the gray point and the y axis indicates the frequency of these intensities. The pectoral muscle's gray levels are greater than those of adjacent tissues [29]. Camilus et al. [47] researched an automatic method to define the pectoral muscle in mammograms of mediolateral oblique perspective using the watershed transformation. The conversion of the watershed of the mammogram shows interesting features including the appearance of a unique watershed line corresponding to the pectoral muscle boundary. Furthermore, the pectoral muscle region is over-segmented owing to the existence of several catchment basins within the pectoral muscle. The Kamila and Justyana researched a completely automatic breast region segmentation algorithm based on two types of global image thresholds: multi-level Otsu and minimizing fluidity measurement, gradient estimation and linear regression [48].

Liu et al.[49] proposed algorithm is based on the pectoral muscle's positional trait in a breast area to combine the iterative Otsu thresholding system with mathematical morphology processing to detect a raw pectoral muscle boundary. Burcin et al.[50] researched Otsu's[51] N thresholding method, an extended version of Otsu's technique of segmentation, where N shows the classes we want to segment in the image. It is a non-parametric, unsupervised technique of automatic threshold choice and only uses cumulative moments of zero and first gray.

B. Region-based Methods: Raba et al. [56][52] suggested a "two-phase" technique for achieving segmentation. Using a selective area growing algorithm, the adaptive Histogram technique was used to differentiate the breast from the background and attain pectoral muscle suppression. The author's suggested technique encompasses the three steps. The first stage is to locate and orientate the breast, then inside the pectoral muscle a seed is put. A statistical region growing algorithm is implemented and the pectoral muscle is lastly suppressed and the border is refined with a morphological operator. N. Saltanat et al. [53] suggested a technique capable of segmenting pectoral muscles in a wide spectrum of sizes, shapes and positions. This algorithm is robust not only for big differences in pectoral muscle size, shape and position, but also for any kind of artifacts such as medical tags.On 322 pictures of the Mammographic Image Analysis Society (MIAS) database, the algorithm was implemented. The segmented findings gave precision to 84 percent and 94

C. percent respectively of the segmentations. Nagi et al. [54]

D. proposed a morphological pre-processing and increasing plant region (SRG) algorithm to avoid digitization noise, suppress radiopaque artefacts, separate background zone from the breast profile area, and finally remove pectoral tissue to accentuate the breast profile area. Nanayakkara et al. [55] explored an automated system to estimate skin line and breast segmentation. The technique proposed for seed area propagation is based on automatic seed region choice and modified fast marching algorithm. Automatic boundary point selection for original border estimation with intensity gradient data. Morphology operators for final boundary estimation and breast tissue area segmentation. The effectiveness of the suggested technique was evaluated using 136 mammographic pictures taken from the mini-MIAS database with all kinds of breast tissues. Results from the experimental assessment show that this algorithm's sensitivity is 99.2% of the surface reality breast area and 99% of the precision of segmentation. Maitra et. Al. [37] investigated the three separate measures to remove pectoral muscles. The initial phase involves enhancing contrast with a limited comparison using the technique of adaptive histogram equalization (CLAHE). Then describe the rectangle to isolate the pectoral muscle from the area of concern (ROI) and lastly remove the pectoral muscle using the design algorithm of our suggested crop region (SRG). The algorithm involves all 322 mammogram images from the MIAS database. It involves all breast shape, size, and type forms including deformities, asymmetries, and faults. The experiment was carried out with fatty tissue, fatty fibro-glandular tissue as well as fibro-glandular tissue. The qualitative measure was taken and in the MIAS database it reached an acceptable rate of 95.71%. Chen and Zwiggelaar [36] submitted the automatic Breast Boundary Identification which is a combine method of mammograms. The technique based on the growing region has been implemented. The seed point was placed near the border between the breast tissue and the pectoral muscle. The boundary point was recognized by drawing a line from the first pixel of the uncurved side into the breast. (slope equal to -1). For the segmentation of the pectoral muscle, almost precise outcomes for the MIAS and EPIC information are accomplished by 92.8% and 87.9% respectively. Rampun at. Al, [14] studied the breast border through thresholding and searched for the border using Active Contour Models without edges.The five edge characteristics were drawn to discover the edge with the greatest likelihood of being the original pectoral contour and searching through contour growth for the real border.

E. Thresholding*:* The principle of thresholding is to fix a threshold T for each and every pixel P of an image I. If the value of P < T then replace the pixel value by zero, otherwise 1. Thresholding is a easy and effective way to divide an picture into a foreground and background. The concept is to divide the picture into two components. Thresholding implies that the picture is converted into binary format. A thresholding method based on histograms is used to divide the region of pectoral muscle. The global optimum in the histogram is chosen as the threshold value [26] but due to the low contrast between pectoral muscle and breast, the thresholding technique has its own restriction. Some writers have created techniques for identifying the breast region on the grounds of a global histogram analysis [25, 62[56], 63[57]]. The Qian et. al, [8] utilizes the method of wavelet transformation to develop segmentation algorithms. The implementation of active contours used by Wirth and Stapinski [58] to extract the mammograms breast region.

F. Gradient Based Approach: An image gradient is an intensity or color change in a picture or image. The border point can be viewed as a stage in an picture in which a discontinuity (in gradient) takes place across a row. A discontinuity can be classified as the Convex and the Concave roof edge, the Concave ramp edge, the step edge, and the Bar edge.Chandrasekhar and Attikiouzel proposed the pectoral muscle border segmentation algorithm [59]. In this work, the author relaxes the constraint that digital gradients should only be directed to the components of the edge vector, and instead allows any combination of edge-sensitive features, including directed digital gradients, suitable for the task at hand. The author also relieves the limitation that mixing vector components to produce a true scalar magnitude must meet the characteristics of a standard and instead of allowing a blending function to map a vector to a true scalar, potentially mixing "norming" and thresholding activities in a single move to produce an "almost" binary image. In this template, two implicit limitations are loosened. By changing the conventional edge detection paradigm to adjustable parametric edge detectors, the pectoral edge was obtained. There were investigations into two guided digital gradients, four neighbourhood-based border characteristics, and two statistical descriptors. The pixels are "stretched out" as a vector w of dimension 9, indexed from 1 to 9 in raster scanning mode, from left to right and from top to bottom in the initial neighbourhood around a target pixel. The absolute scores of the digital gradients of the horizontal and vertical Sobel and the variety and standard deviation as shown below have been described below.

$$\varphi_h(\omega) = |(\omega_9 + 2\omega_8 + \omega_7) - (\omega_1 + 2\omega_2 + \omega_3)| \qquad (1)$$

$$\varphi_v(\omega) = |(\omega_3 + 2\omega_6 + \omega_9) - (\omega_1 + 2\omega_4 + \omega_7)| \qquad (2)$$

$$\varphi_r(\omega) = \max_{1<i<9}[\omega_i] - \lim_{1<i<9} \omega_i \qquad (3)$$

$$\varphi_s(\omega) = \sqrt{\left[\frac{1}{9}\sum_{i=1}^{9}\omega_i^2\right] - \left[\frac{1}{9}\sum_{i=1}^{9}\omega_i\right]^2} \qquad (4)$$

To guarantee that the ranges of the distinct characteristics are compatible, each is standardized so that the range of the four is (0,4). The author studied the selection options for the blending function and clarified the sigmoid blending function, as the logistic function is appropriate for pectoral edge detection. In one dimension, the logistical function has the shape where λ and β are real, positive constants.

$$b_L(x) = \frac{1}{1 + \exp(-\lambda(x - \beta))} \qquad (5)$$

The authors visually evaluated the results and the pectoral edge detection algorithm took the best combination of features, logistical parameters and standard. The selection of t = 1, λ = 100 and β = 0.5 for the blending function bL provides the surface of the pectoral tissue with a sensitive and safe segmentation.

Molinara et al. launched a new pectoral muscle recognition approach that uses the pre-processing phase to normalize the image and draw attention to the muscle-mammary tissue border. Edge detection and regression through RANSAC also provide the muscle area's ultimate contour. A set of 55 randomly gathered pictures from a freely accessible database called the Digital Screening Mammography Database (DDSM) assessed the technique [11].All pictures are related to the MLO perspective of nearly 3500× 6000 pixels in size. The Gaussian filter used in the smoothing phase was made using a matrix of n × n kernel with n = 171 and σ = 26. The RANSAC algorithm was implemented to separate outliers and inliers, considering 500 points as an inlier minimum and 10 pixels as a limit at boundary. In the experiment the 55 Images has been taken. In the result the accuracy was 89.1% while 10.9% was inaccurate. The compared approaches are the method by Kwok et al. [20] that proposes an iterative thresholding together with a gradient-based searching with 83.6% accuracy, a statistical method based on AD measure [57] with 81.0% accuracy, the work of Mustra et al. [60] proposed an hybrid with bit depth reduction and wavelet decomposition with 86.0% accuracy and an adaptive histogram method suggested by Raba et. al, [34] with an precision of 86.0%.

G. Transform Based Methods

Texture feature is an important feature of the low-level image. It can be used to define the content of an image. Image texture examines information on spatial arrangements of color or intensity in a image. Using Gabor wavelets, dyadic wavelets, Hough transform and Radon transform, etc., the texture function and variation in intensity can be noted by decomposing the complicated picture into basic form [61]. The intensity level variation can be helpful for the radiologists to understand the mammography image more accurately. Due to its in-built capacity to acquire spatial frequency data from pictures, wavelet-based segmentation techniques were used to extract characteristics from mammograms [29]. To obtain the spatial frequency information the wavelet based segmentation method have been used in mammography[62]. Mencattini, Arianna, et. al,[63] Proposed the algorithm for image denoising and enhancement that based on dyadic wavelet processing. The estimation of local iterative noise variance was used to denoise. The author outlined an adaptive enhancement tuning on separate wavelet scales, while a new segmentation technique combining dyadic wavelet information with mathematical morphology was developed in the case of mass detection. Ferrari et al. [67][64] used Gabor wavelets to explore the method of multi-resolution. The Gabor filter was intended to enhance the surface of the pectoral muscle, with pectoral muscle containing the region of concern. The ROI is extracted with geometric and anatomical constraints:

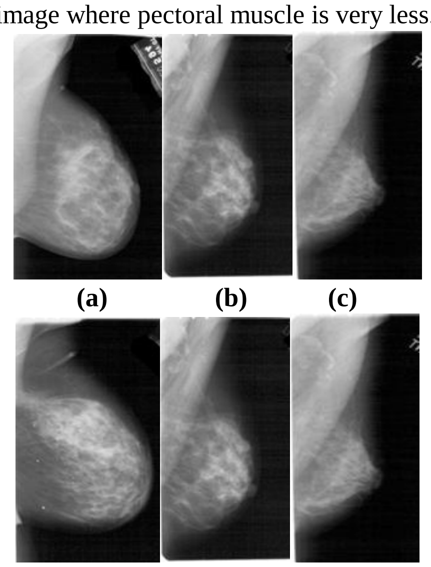
(1)The pectoral muscle is measured as straight line which is restricted to the angle 1200 and 1700 at lower right corner of the rectangular box by equation:-

$$R_i = \{(x,y): 0 \le x < nx/2, 0 \le y < ny/2\} \quad (6)$$

(2) The pectoral muscle appears with thick area almost similar gray-level scores with the Gaussian kernel. To recognize the original pectoral muscle border, Li et al.[65] studied the homogeneous texture and high-intensity deviation technique. For the refining of the ragged original edge, further Kalman filter is used. The results of the test show the precision for the mini-MIAS database and the DDSM database of 90.06 percent and 92 percent. The Gabor filter technique is used for enhancement of directional and piecewise-linear structures [31] [66] [67]. Ma et.al, [68] propose a border detection system based on “edge flow”. Using the predictive coding model, the Edge Flow method identifies and incorporates the shift in direction in picture characteristics such as discontinuities of color, texture and phase at each place. It is feasible to identify boundaries in picture fields that find two opposite stream routes in stable state by propagating the edge flow vectors.

H. Active Contour Method

Akram et. al, [69] proposed stopping algorithm using active contours to obtain the contour that contains the pectoral muscle boundary. The binary image was obtained from the pectoral muscle contour. Using binary image of pectoral muscle and the initial mammogram picture, the required picture without any pectoral muscle and artefacts was obtained. In the first step threshold value T=15 have been applied to convert image into binary image. The pectoral muscle border is identified using Mumford Shah model-based multiphase ' active contour method. The suggested algorithm given mini-MIAS database 97.84 percent precision. Mughal et al. [70] suggested technique not based on the notion of straight line to detect pectoral muscle elimination. The separate operator of differentiation was used to extract the pectoral muscle and approximate the intensity function gradient value. A precise edge border of the breast body is also determined. A convex picture is produced using the end point of the walls of the breast body. Eventually, a convex hull function is built to create a topographic map using convex image and boundary tissue to eliminate the pectoral muscle. The suggested method is applied to the MIAS dataset to obtain high accuracy in the various dimensions of pectoral muscles for a 322 mammograms and 20 contrasts improved digital mammographic pictures. The traditional effective deformable contour model was studied by Ferrari et al. [71] to detect the breast border. Algorithm applied the logarithmic operation followed by Lloyed-Max algorithm. The energy lavel has been minimised by applying the greedy algorithm developed by Williams and Shah (1992) [61] although the active contour models reported excellent achievement in pectoral muscle removal and other breast areas But there are certain constraints, such as noise, fragile edges, amount of inner parameters, local minima lost at convergence time, lacking data about the range between the two pixels, which can be a barrier to define the pectoral muscle boundaries. Lei et al. [72] propose the technique that is based on a discrete time Markov chain (DTMC) and an active contour model to detect the edge of the pectoral muscle. The model includes two significant pectoral muscle edge features, i.e. continuity and uncertainty. In the below given images it is clear that intensities of the pectoral muscle are changing .In some images pectoral muscle is mixed with glandular tissues and there is a image where pectoral muscle is very less.



(d) (e) (f)

Fig. 5. Various Mammograms Images Where The Shapes And

The Intensity Contrsts Of Pectoral Muscles Changes Greatly

In the Fig 5(a) The Pectoral muscle border in the lower part has a curved and vertical shape. In Fig 5(b) The density of the pectoral muscle is substantially increasing.In Fig 5(c) The pectoral muscle region is larger than the breast region. Fig. 5(d) the area of the pectoral muscle is very small and its boundary is nearly vertical in the lower part. Fig. 5(e) the glandular tissues and pectoral muscle is mixed in the lower part of the breast thus edge detection of the pectoral muscle is very tough. The Fig 5(f) is also very complex where several layers of the pectoral muscle exist and also these muscles are changing the intensity greatly. These are the few complex cases where exact boundary detection is tough [72]. The pectoral muscle's rough border was identified using Markov's discrete time chain. To refine the detection results after acquiring a rough border, an active contour model is implemented. The pixel ratio of true favourable (FP) and fake negative (FN) is less than 5 percent in 77.5 percent mammograms. The 91 percent detection accuracy meets the clinical necessity.

I. Graph Theory Methods

Cardoso et al. [73] studied the algorithm based on a graph's shortest route. The polar coordinates were used to identify the route between the image's lateral and top margins. The edge weight connecting 4-neighbour pixels p and q have been calculated by the formula.

$$f(g) = f_l + (f_h - f_l)\frac{\exp(\beta(255 - g)) - 1}{\exp(\beta\ 255) - 1} \quad (7)$$

The algorithm was tested on 100 images which have been collected from Hospital S. Jo˜ao Porto, Portugal and the 50 images have been fetched from the DDSM database. Hausdorff Distance has been calculated by the expert which was 0.1387 and 0.1426 for the DDSM and HSj Database respectively. The mean distance was 0.0545 and 0.0387 for DDSM and HSJ Database.The fast growth of graph theory based picture segmentation has become a study focus in latest years. Each image is mapped to a weighted graph G=(V, E) where ' V ' is a set of nodes corresponding to separate image pixels, and ' E ' is a set of node edges. The Minimum spanning trees and finding the shortest path through graph theory have shown the important role in the area of image segmentation. Fei Ma et al. [74] explored two methods. The first technique is based on adaptive pyramids (AP), while the second technique is on minimal spanning trees (MST) as submitted by Felzenszwalb and Huttenlocher [75]. The public data set was used to test the mammogram algorithm. It is a difficult job in picture segmentation to decide whether or not a particular pixel should be included as the part of the item of interest. To assess the full path of a border, local information is required. Global information is desirable to determine which edge or lines in the image should be considered as limitations and how to link them. The methods implemented with 84 mammogram images from mini MIAS database. The efficiency is based on average distance error measurement between real and computed boundary. It is found that the average error by the AP and MST algorithms is less than 2 mm for 80 percent of the images and less than 5 mm for 97 percent of the AP images.

J. Geometry-Based Method

Taghanaki and et. Al, [76] implemented a Geometric rule-based algorithm specifying the segmentation of the pectoral muscle forms Normal, Convex, Concave and Combinatorial. This technique promotes pectoral muscle segmentation without limiting the breast or muscle size. The method was tested on total 872 Images which have been taken from three datasets. The three dataset are INbreast (197 Images), Image Retrieval in Medical Applications (IRMA a version of DDSM 353 Images) and MIAS Database from where 322 images has been taken. The coefficient of Jaccard ndex and Dice similarity was determined to evaluate the segmentation algorithm which have been defined as below

$$Jaccard = \frac{|R_a^i \cup R_m^i|}{|R_a^i \cap R_m^i|} \quad (8)$$

$$Dice = \frac{2|R_a^i \cap R_m^i|}{|R_a^i| + |R_m^i|} \quad (9)$$

K. Soft Computing Based Methods

Aroquiaraj and Thangavel [77] discussed the challenges because of fuzziness of image objects and overlapping of the different images. The author discussed various operator for edge detection like Laplacian of Gradient , Roberts, Sobel , Prewitt , Canny and Log edge to get the idea about boundary. A technique combining genetic algorithm with morphological selection algorithm discussed by Shen at al.[31] which includes the pre-processing, genetic algorithm, Selection of morphology and curve fitting. The Method achieves an average rate of FP and FN of 2.03 and 6.90% (mini MIAS), 1.60 and 4.03% (DDSM), and 2.42 and 13.61% (INBreast) respectively.FP and FN rate have been explained for three result categories which is given in Table: I

Table I. The FP and FN rate of different categories

Category	Criteria
Successful	FP ≤ 0.1 and FN ≤ 0.1
Acceptable	Min(FP,FN) ≤0.1 and 0.1max(FP,FN)≤0.2
Unacceptable	FP>0.2 or FN >0.2

L. Adaptive gamma Corrections Method

Gardezi et al. [17] projected the Adaptive gamma correction for finding the edge of the pectoral muscle. Interpolation equation is used to detect missing points in the boundary of pectoral muscle and detects 98.45% of pectoral parenchyma.

The (Table II) shows the various assessment score by experts for the results in MIAS and with other database.

Table: II Various methods and their results

Author/Year	Method	Database	No. of Images	Results	Advantages
Kwok et al.(2004) [7]	Estimated by a straight line further refined by cliff detection	MIAS	322	The Expert mammographic radiologists, assesses results by rating curve segmentations with 83.9% which is adequate or better.	The algorithm adapts to differences in the size, density and curvature of the pectoral muscle.
Ma et al.(2007) [77]	i)Adaptive Pyramids ii)Minimum spanning Tress iii)Active Contours	MIAS	84	Average error for AP and MST less than 2 mm for 80% And less than 5 mm for 97% of pictures for AP.	The boundaries discovered by AP and MST are sufficiently precise to serve as the original reliable.
Cardoso et al. (2010) [76]	Shortest Path Method	DDSM	50	Hausdorff Distance was 0.1387and Mean Distance was 0.0545	Results were good among the graph-based techniques, but the algorithm may select the incorrect one in case of various powerful edges.
		FSJ Hospital Data	100	Hausdorff Distance was 0.1426 And Mean distance was 0.0387	
Chakraborty, Jayasree, et al. [60]	Using Average Gradient and Shape Based Feature	MIAS	80	Average FP and FN pixel percentages are 4.22%, 3.93%, 18.81%, and 6.71%, 6.28%, 5.12% for mini-MIAS, DR, and CR images, respectively.	method outperforms the other two algorithms in terms of total mismatched pixel percentage, Housdorff distance, and MDCP.
Taghanaki et al.(2017) [79]	Geometry based Model and adaptive RG	MIAS	322 (4 images without pectoral muscle)	95%	Result tested on all BI-RADS tissue density classes. Techniques help all manner of pectoral muscles like (Concave, Convex or their combination)
		DDSM	353	94%	
		INbreast	197	96%	

Shen et al.(2018) [31]	Genetic Algorithm and Morphological Selection	MIAS	322	96.89%	Pectoral muscle segmentation has been effective in 291 mammograms and 21 images have been found appropriate. The 10 images were unacceptable.
Gardezi et al.(2018) [33]	Adaptive gamma corrections	MIAS	322	98.45% with the 92.79% average Jaccard similarity index.	Segmentation of pectoral muscle was successful with the interpolation equations.

III. MOTIVATION

Pectoral muscle segmentation is a challenging task due to variation in size, shapes and intensity decomposition. For further study and early detection of breast abnormalities, automated identification and segmentation of pectoral muscle in the mid-lateral oblique view of mammograms is necessary.

IV. CONCLUSION

The discussion seen in the above segments indicates that there isn't any specific technique which works fully well for the problem of pectoral muscle segmentation. In most situations, the solution given concentrates more on a particular collection of information or a particular issue in hand. For pectoral muscle detection, few generic solutions are accessible. As a consequence, the findings obtained from accessible study articles are very hard to quantify.

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