An Improved Segmentation Technique Based on Delaunay Triangulations for Breast Infiltration/Tumor Detection from Mammograms

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Abstract— **Breast tumor segmentation and analysis is an important step for doctors in deciding the stage of cancer and to proceed for further treatment. Segmentation of image is a crucial step in image processing which further helps in classification of image based on the features extracted. The segmentation technique in most of the approaches uses similar kind of algorithm for segmentation of region of interest. This paper presents a new approach for preprocessing and segmenting out the infiltration and tumor regions from digital mammograms using two techniques involving iterative and non iterative algorithms of Delaunay triangulation. The preprocessing involves hybrid filter for noise removal and image enhancement. The iterative algorithm for segmentation works to get an idea of shape of infiltration/tumor in the breast. The proposed algorithm uses Voronoi properties to partition an image into regions of similarity followed by Delaunay triangulation. The advantage of this technique is it works on the histogram of the image instead of the entire image hence it is effective for large sized mammograms reducing the load on algorithm. This is fully automated and unsupervised process. No parameter is needed for segmentation which is an advantage over other popular segmentation methods like k-means and watershed. The Voronoi and Delaunay segmentation are region growing method which looks for similarity in the images and segment outs the high intensity region (in this case the probable infiltration/tumor) from the entire image. We also propose divide and conquer algorithm for Delaunay triangulation to get faster output (average execution time is 0.4 sec). To evaluate our proposed method a comparison with k-means and watershed segmentation and the results of feature extraction is carried out.**

Keyword- Digital mammograms, Breast infiltration, Breast tumor, Delaunay triangulation, Voronoi properties, Unsupervised

I. INTRODUCTION

The early detection and treatment of breast cancer is crucial for reducing mortality [11]. The calcifications/tumors of the breast may be intra mammary, around the ducts, in the vascular structures or in interlobular connective tissue [10]. The challenge is to employ computer aided detection (CAD) techniques for the purpose of assisting radiologists in the early detection of cancer, by processing and analyzing images [1], [10]. In this paper we propose a novel integrated approach for preprocessing and segmentation of breast malignancy in mammograms. The preprocessing involves noise removal and image enhancement, which is achieved by a hybrid filter and CLAHE (Contrast limited adaptive histogram equalization technique). The segmentation technique proposed in this paper is a different and unique from the usual k means and watershed segmentation methods as our method is based on region growing technique and it is iterative, automatic and unsupervised process which works on the histogram of the image unlike other which works on entire image. Delaunay based segmentation and feature extraction is done using CAD technique for prognosis of ER+ breast cancer in histopathology of each image [18], [19]. Our algorithm is tested on real time mammograms.

II. PREPROCESSING

It involves identifying the source of noises and their removal by the best filtering technique [12], [13]. The common noises present in the mammogram are salt & pepper, speckle, Gaussian and impulse noise [1], [13]. We propose a hybrid filter as a combination of adaptive median and wiener filter for noise removal and image enhancement [3]. The enhancement is achieved by using CLAHE which is efficient in improving the contrast and making the medical image more informative[14].

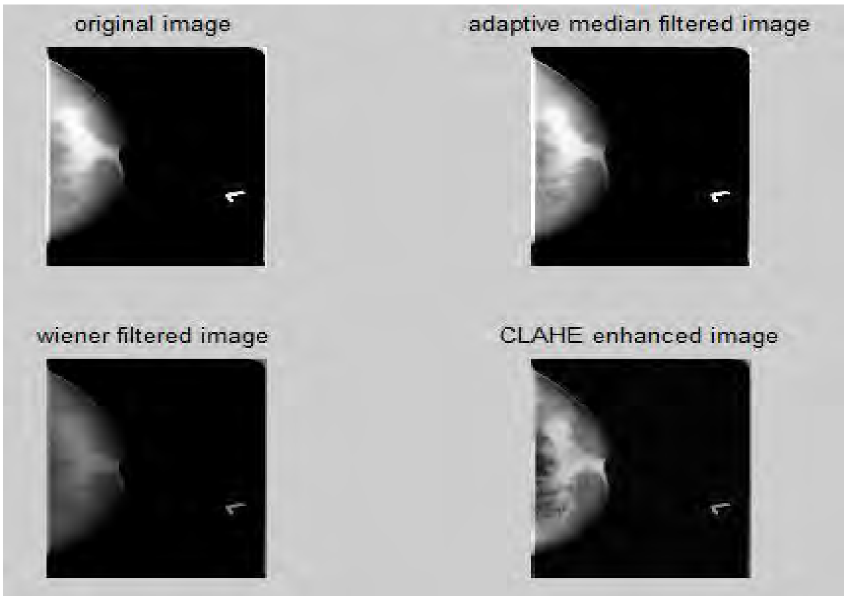

Figure 1 :The output of hybrid filter and CLAHE

III. IMAGE SEGMENTATION

The segmentation of image is a fundamental step in image processing. Image segmentation essentially affects the overall performance of any automated image analysis system thus its quality is of great importance. Image regions, homogeneous with respect to some usually textural or color measure, which result from a segmentation algorithm are analyzed in subsequent interpretation steps [17]. Literature review suggested there exists various approaches on mammogram segmentation [22], [23] however the attempts to generalize segmentation approaches proved ineffective as these methods work correctly only for specific type of images. The proposed method of Delaunay triangulation of segmentation works on the histogram of the image unlike k-means and watershed, which works on the entire image. K-means segmentation requires setting of the parameter initially whereas Delaunay method does not requires any initial setting of parameter. Watershed segmentation on the other hand leads to over segmentation and hence the output does not appear meaningful. A comparative result of the proposed method with k-means and watershed can be seen in the Figure 9, 10 and 11. Our algorithm's output displays a message box shown in Figure 12 for Delaunay based segmentation without iteration, showing number of gray levels. Also in iterative Delaunay based segmentation a graph is displayed [Figure10(c)] plotting number of clusters and execution time. Most of the research done related to mammograms aims towards the computer-aided detection of mammogram tumors, which gives the classification of mammograms [21]. The size, shape, features of an image aids in classification of image [7], [17].

Voronoi diagram/tessellation

VD or Voronoi tessellation is a well-known technique in computational geometry, which generates clusters of intensity values using information from the vertices of the external boundary of DT (Delaunay Triangulations)[3]**.** Voronoi diagram is a prominent way of dividing any space into regions. VD set of "sites" (points) is a collection of regions that divide up the plane. Each region corresponds to one of the sites and all the points in one region are closer to the corresponding site than to any other site[3].

Voronoi diagram (VD)'s characteristic-[as shown in Figure(1)]

- Each vertex of VD (P) has 3 degrees.
- The circle passing through the 3 points defines a vertex and it does not contain any other point.
- The locus of the center of the largest empty circles passing through only a pair of points Pi, is the edge of the diagram.
- The locus of the center of largest empty circles passing through only one point, defines a cell. Seed point is selected based on threshold and the image is divided into regions according to the Voronoi diagram, after this the classifier reclassifies it to boundary, interior or exterior [2].

Delaunay Triangulation (DT)

For a set P of points in a plane, Delaunay triangulation corresponds to triangulations or subdivision of a geometric object into triangles. Such that for the triangle has no point in P inside the circumcircle of any triangle in DT (P). Delaunay triangulation of a discrete point set P corresponds to the dual graph of the Voronoi tessellation for P [Figure 2].

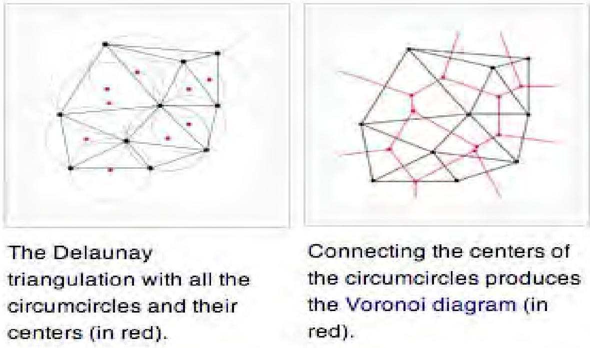

Figure 2: (a) left- Delaunay triangulation (b)right- Voronoi diagram
(Courtesy: http://en.wikipedia.org/wiki/Delaunay_triangulation)

IV. METHODOLOGY

The preprocessed images are then segmented to bring out region of interest after which the features of the extracted part help the doctor to analyze the class and stage of the cancer, which aids in further treatment [21]. Voronoi polygons may be viewed as the result of a growth process. The Voronoi diagram, together with the incomplete polygons on the convex hull defines a Voronoi tessellation of the entire plane. The collection of edges obtained by joining each point with its neighbors is the dual of the Voronoi tessellation and is called the Delaunay triangulation [8].

Algorithm:-

- A Delaunay graph GD = (V, ED, WD) [Figure 2] is a sub graph of G that is easily calculated from the Voronoi Diagram R.
- Each R is defined in a set of polygon P
- P = {P (v1), P (v2),...,P(vn)} surrounding all nuclear centroids V.
- Each pixel c ∈ C is linked to the nearest v ∈ V (via Euclidean distance) and added to the associated polygon P (v) ∈ P.
- Therefore, graph GD of Delaunay is simply the dual graph of R and is constructed such that:-
- If P (va), P (vb) ∈ P share a side, their nuclear centroids va, vb∈ V are connected by an edge (va,vb) ∈ ED.

The duality comes in the following way [5,9]:

- Vertices in the Voronoi diagram corresponds to infiltrations or tumors in Delaunay Triangulation, while Voronoi cells correspond with vertices of DT.
- After the Voronoi diagram for a set of points is constructed, Delaunay Triangulation is produced by connecting any two sites, whose Voronoi polygons share an edge.
- More specifically: let P be a circle free set. Three points, *p*, *q* and *r* of P define a Delaunay triangle if there is no further point of P in the interior of the circle which is circumscribed to the triangle *p*, *q*, *r* and its centre lies on a Voronoi vertex[Figure. 3]

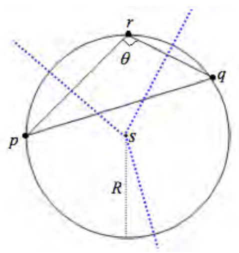

Figure 3: Delaunay construction. *Pqr* defines a Delaunay triangle when the centre (S) of the circle circumscribed to *pqr*is a Voronoi vertex. (Courtesy-[5]).

Y. Xiao And H. Yan, [4] firstly obtain Delaunay triangulations from points of an edged image. Each triangle's property was geometrically examined thus identifying J-Triangle (Junction triangle). J-triangles repair the broken edges by acting as linkers. The objective of this is to prevent the object boundary from being merged with the background. The method used by them results into heavy computational load and thus is ineffective for mammogram as they are large sized. It is also not efficient for some mammographic cases as the algorithm might get puzzled over the infiltration cases or improper illumination images. It has limitations in cases of rotation and is also sensitive to noise. The demonstrated success rate for detection of features upon segmentation by method of [4] is 89%. In contrast, the proposed method of ours uses the Voronoi diagram and its properties to a select some unique feature points that are derived from the histogram of mammogram rather than on points corresponding to the edges. Our computational process is much less than that of the method proposed in [4].

V. PROPOSED METHOD

Firstly, histogram equalization is performed so as to reduce the improper or ill lighting in mammograms. Next, the Voronoi Diagram (VD) is applied. In various literature studies, Voronoi diagram is applied on the image itself by capturing the edges of the image after binarising it. This is usually time consuming and gives a lot of load on the algorithm therefore, we propose our idea to apply Voronoi Diagram on a few selected points (less than 255) instead of the entire image. This also prevents loss of information as histogram is used to select the point which corresponds to tumor and infiltration which are an abrupt change in intensity compared to neighboring pixels.

From the points on the image, Voronoi diagram is used to construct Delaunay triangulations (DT) from points on the image histogram. The outer boundary of Delaunay triangulation is simply the Convex Hull (CV) of the set of the feature points.

Convex hull

It is the smallest convex set that contains a set *X* of points in the Euclidean plane. Here convex set is a Euclidean plane, in which every pair of points is within the object, every point on the straight line segment that joins them is also within the object. Thus the two global maxima are obtained by extracting the top two values in the Delaunay triangulation list of vertices, which refers to the histogram's peak. To obtain the minima, which falls between these two peaks, a new set of points, are created using the following steps:

- Generate the histogram of mammogram.
- Generate Voronoi Diagram /Delaunay Triangulation to obtain the list of vertices and get the two peaks.
- All points below the first peak are set to zero, and all points beyond the second peak are set to zero.
- All points that are equal to zeros are set equal to the argmax *(peak1,peak2).*

Here, argmax =argument of the maximum. It gives a position peak2_max at which peak1 is maximized

New points are derived using:

$$Val\ new\ (x) = |\ (Val(x) - max\ (Val(x)))\ |$$

Here, *max (Val (x))* denotes the highest frequency in the histogram of mammogram. This process will yield a local flip effect on the image and continues to flip edges until no triangle is non-Delaunay.

Delaunay condition

The triangles ABD and BCD meet the condition, if the sum of the angles α and γ =< 180. If two triangles do not meet this condition, common edge BD is switched for the common edge AC to produce two triangles that meet the Delaunay condition [Figure 4].

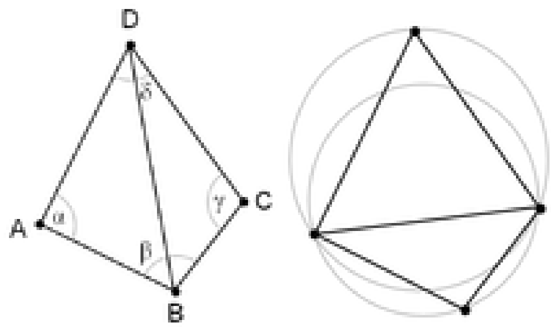

Figure 4: (a) left- non-Delaunay triangulation (b) right- non Delaunay triangulation turned to Delaunay triangulation by local flip effect (Courtesy [5]).

This will expose minima points to be part of the convex hull constructed by Delaunay triangulation. These unique feature points are then sorted in ascending order to outline a one-dimensional vector (V) containing values that form the ranges with which merging and splitting decisions are made.

VI. RESULTS AND DISCUSSIONS

The proposed algorithm is evaluated on the basis of comparisons done with different approaches for segmentation and from the values obtained from feature extraction ,applied on the region of interest . Features extracted for various images of breast consisting cancer. The results of features obtained from k-means clustered image,watershed segmented image, and our proposed Delaunay triangulation(iterative and non-iterative) for 5 images of breast consisting tumor or infiltration is tabulated below: (where PT=Patient).

The features we have extracted and compared are:

Mean:-

The mean of the pixel values in the defined window, estimates the value in the image in which central clustering occurs.

Standard Deviation:-

The Standard Deviation (σ) is the estimate of the mean square deviation of grey pixel value p (i, j) from its mean value. Standard deviation describes the dispersion within a local region. (Image size M*N).

Moment:

It gives the measure of homogeneity of the image.

Skewness:

Skewness, characterizes the degree of asymmetry of a pixel distribution in the specified window around its mean. Skewness is a pure number that characterizes only the shape of the distribution.

Kurtosis:

Kurtosis, measures the peak or flatness of a distribution relative to a normal distribution.

Table I: Feature extraction results from watershed segmentation

	MEAN	STD	MOMENT	SKEWNESS	KURTOSIS
PT1	1040.1367624	2370.0047679	331.1372120	66.03939476	22.19565918
PT2	1033.8277263	2302.2917353	216.86774419	220.62306302	57.32014717
PT3	1478.2499138	2742.5739371	4405.11042802	48.167404903	8.066108616
PT4	380.06840635	1051.7511765	13422.1572203	286.27023047	8.982228133
PT5	2858.7686225	6491.773538	686.7421309	38.62934233	32.71427382

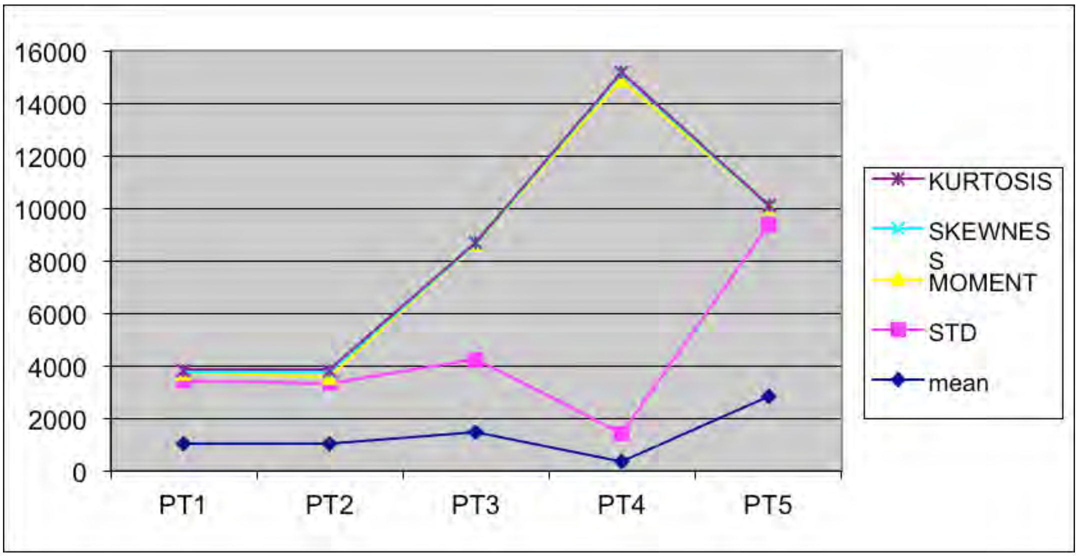

Figure 5: Line plots of all the parameters taken for feature extraction using watershed segmentation

A graph is plotted of feature extraction by watershed segmentation, for the 5 parameters for 5 patients [Figure 5]. By comparing the results with other graphs we can see that except mean all other parameters shows variation. Standard deviation, which defines dispersion within local region, varies largely for the 5 images and is lowest in watershed segmentation from which we can observe that the result leads to over segmentation.

Table III: Feature extraction results from k means clustering

	MEAN	STD	MOMENT	SKEWNESS	KURTOSIS
PT1	3512.4488464	15389.66455	468.87871801	71.68523462	38.41964735
PT2	3320.9983680	15903.54869	635.78324465	79.42564394	126.8965740
PT3	3249.2356261	14510.14810	377.163899591	69.52695740	89.12318939
PT4	2828.7772199	15548.096801	50.0092523516	73.30031749	176.6304441
PT5	2658.8300372	14698.55139	565.930113189	89.03056731	79.01087568

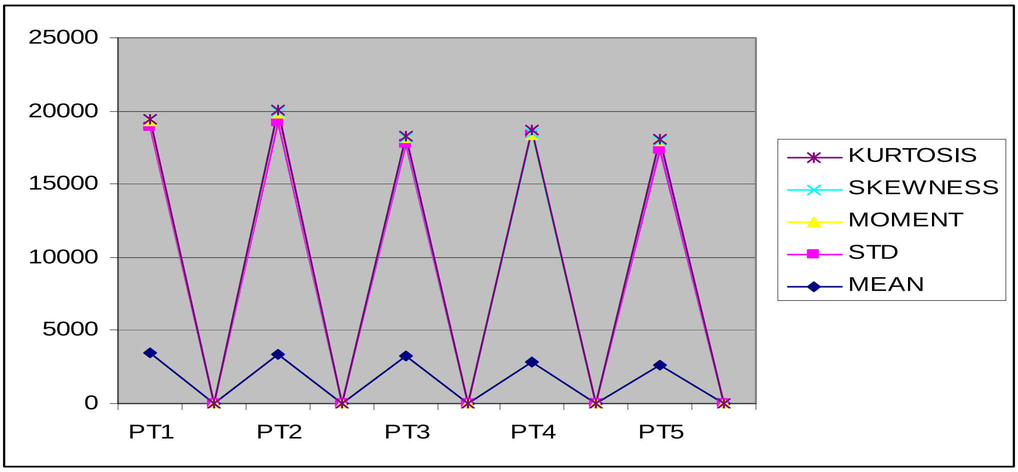

Figure 6: Line plots of all the parameters taken for feature extraction using k-means clustering

From the resultant line graph of the parameters extracted by k means clustering method, we can observe that the mean value in all the cases and all segmentation techniques remains almost the same, however the moment value in k means differs from the moment values in Delaunay method by large difference which shows that in k-means method large area of the image is considered as homogenous one (eg. For patient 5 moment value in k means is 565.93, watershed is 686.74 and for Delaunay it is 9.6322) and k-means method is not that effective in differentiating image into regions of similarity. The performance of k means depends on initial clustering values and it has the disadvantage of requirement of prior selection of parameter, which might lead to human error.

Table IIIII: Feature extraction results obtained from non iterative Delaunay Triangulations segmentation

	MEAN	STD	MOMENT	SKEWNESS	KURTOSIS
PT1	1920.9395926	16750.228369	2.1535448716	135.94405301	158.25120504
PT2	1669.6765337	17956.933522	2.450200921	130.46932433	95.36855864
PT3	2004.9927028	15572.22282	1.504647809	121.08118264	95.381178451
PT4	1899.9605859	15330.466802	1.08969791	110.89770638	184.78912832
PT5	2187.8227635	14002.377847	1.11521802469	131.76717775	101.42694271

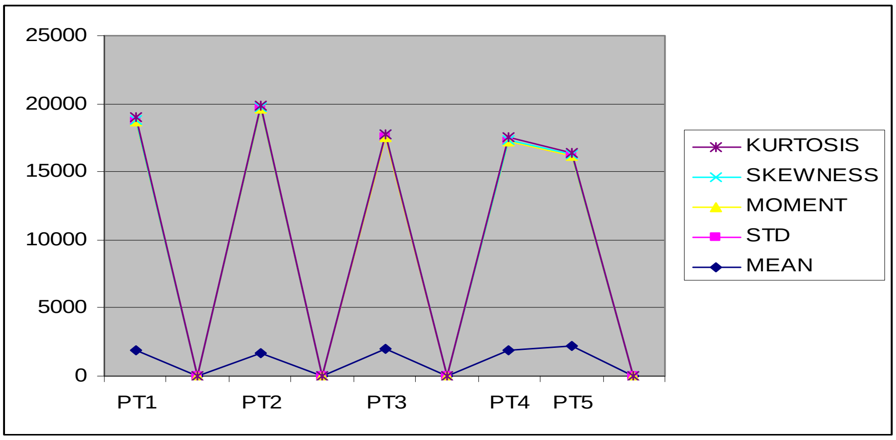

Figure 7: Line plots of all the parameters taken for feature extraction using non-iterative Delaunay

Comparing the resultant values and graphs of different segmentation technique we can say that Delaunay base algorithm for iterative and non iterative segmentation differs from each other in some extent (for eg. The kurtosis (peak and flatness) value for patient 5 in case of non iterative is 101 and in iterative it is 112.76 whereas it is 79 and 32 in case of k-means and watershed respectively) and also in skewness which determines the degree of asymmetry around the mean, the value for Delaunay is much higher compared to those of k-means and watershed when the mean is almost same for all the segmentation methods.

Table IV: Feature extraction results obtained from iterative Delaunay Triangulations segmentation

	MEAN	STD	MOMENT	SKEWNESS	KURTOSIS
PT1	2289.2472024	14364.375827	1.597158417	145.9246317	82.969880784
PT2	1986.0462257	14771.447741	1.4687973016	134.65557812	54.540443665
PT3	2183.5627126	14076.553346	1.325074109	131.6536093	91.421142400
PT4	1881.2170509	14441.707974	1.0891386139	117.2081134	178.93719280
PT5	2158.8400821	13161.737334	9.6322638764	132.3963950	112.76855735

By comparing the line plot graphs [Figure 5,6,7,8] we can say that iterative Delaunay gives an accurate value for all the parameters of the 5 images. The mean for all the images in all the segmentation techniques remains almost the same however there is slight difference in the values of iterative and non-iterative Delaunay based segmentation. The results obtained from watershed segmentation is poor compared to others in terms of kurtosis, skewness and moment and the results generally leads to over segmentation of image as its moment value is high which means it segments the image into number of regions, whereas the results from the proposed Delaunay based method can be considered as more appropriate as the algorithm works on the image histogram instead of entire image and hence there is less chance of getting false negative results.

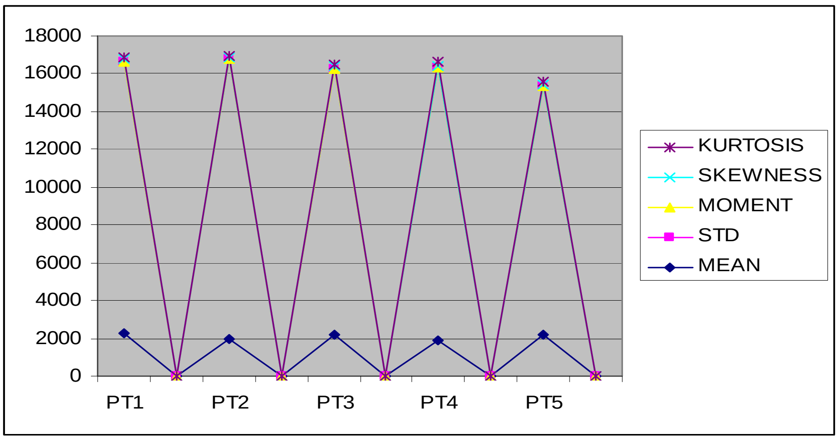

Figure 8: Line plots of all the parameters taken for feature extraction using iterative Delaunay

The region of interest obtained after segmentation has unique role in categorizing of images, like for breast images feature extraction will further aid in classification of image as normal or abnormal, which can be further, classified as benign or malignant [15,20]. Output also displays execution time, which is within 1 second for all mammograms. For Figure 11c, execution time=0.3600 sec. By comparing the results obtained from the common approaches to segmentation techniques and the proposed Delaunay method [Figure 9, 10, 11], we can say that accuracy is more in case of Delaunay based segmentation as it is automated, unsupervised which means it does not require setting of any initial parameter for clustering unlike k-means. It is superior to watershed segmentation as watershed segmentation segments the region based on contours [16] it always does not give meaningful results due to over segmentation. The features extracted from the image can be further used to classify or segment the images [7].

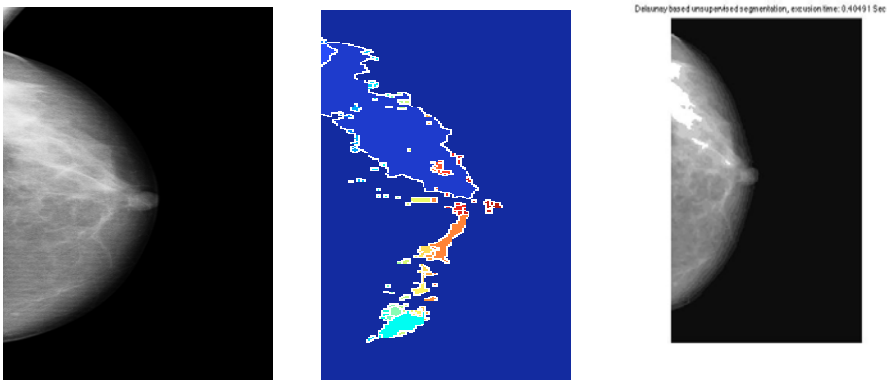

Figure 9: (a) Original image (b) Watershed segmented image (c) Delaunay segmentation without iteration

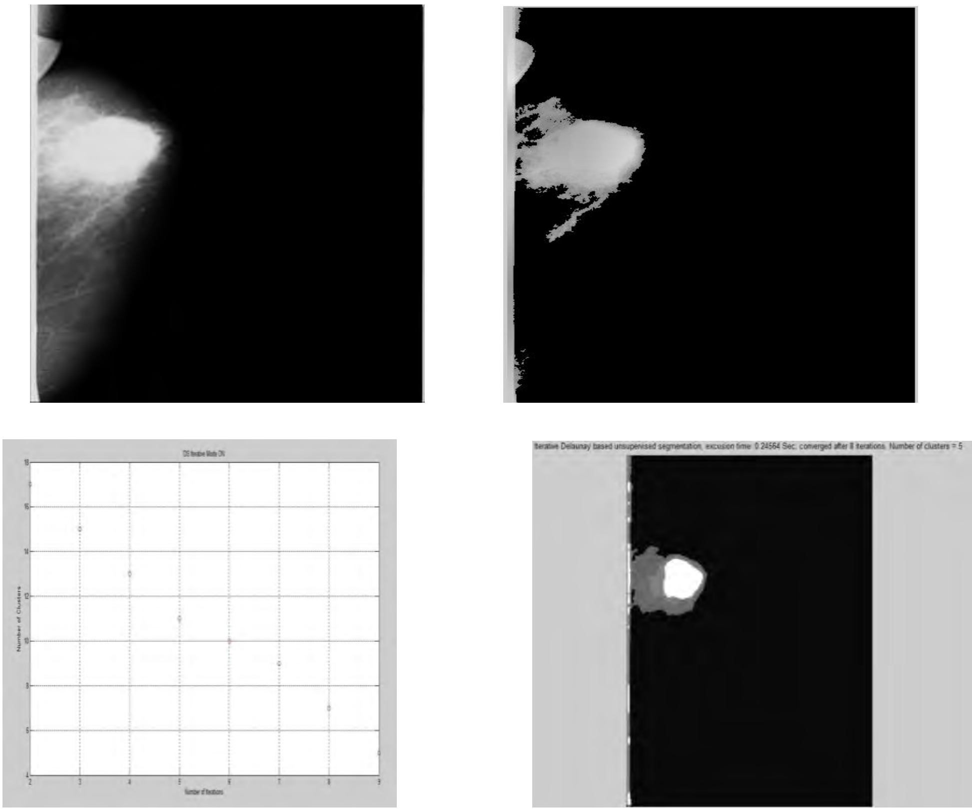

Figure 10: (a) Original image (b) k-means clustered image (c) Graph obtained from iterative Delaunay segmentation (d) Segmented region obtained from Delaunay segmentation with iteration

Figure 11: (a) original image (b) k-means clustered image (c) Delaunay segmentation without iteration

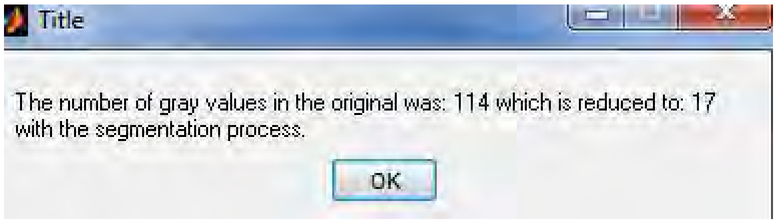

Figure 12: Message box displays number of gray levels in non-iterative Delaunay segmentation.

Table V: Comparison of Image Segmentation Method

Segmentation technique	Method	Advantages	Disadvantages
Histogram thresholding	Image has various peaks and each corresponds to specific regions.	1. Works with low complexity. 2. Does not require prior information of the image.	1. Does not consider spatial details of an image. 2. Not good for images without peaks and clear details.
K means clustering	Works on the assumption that each region is a specific cluster and segments accordingly.	1Easy implementation. 2.Supervised learning	1. Problem in determining number of clusters. 2. Segmented region is not always region of interest.
Edge detection	Based on discontinuities in the image, and segments the regions based on abrupt changes in the pixel values.	Works well for images having good contrast between different regions.	1 .Not give efficient result in image with too many edges. 2. Non-trivial in producing closed boundary and curve’s.
Watershed	Segments the region on basis of contours separating different intensity regions.	1. Simple and fast. 2. Gives better result in low contrast and week boundary areas.	1. Leads to over segmentation. 2. Sensitive to noise.
Voronoi and Delaunay	Based on region growing by partitioning image into different subsets with similarity.	1. Unsupervised. 2.Automatically iterates until accuracy reached. 3. Works on the histogram of the image. 4.No need to set any parameter for clustering.	1. Takes time for iteration. 2.If applied on entire image may increase computational complexity

VII. CONCLUSION

In this paper we have proposed divide and conquer algorithm for Delaunay triangulation to get faster output (average execution time=0.4 sec) as our method recursively draws a line to split the vertices into two sets and for each set, Delaunay triangulation is computed followed by merging two sets along the splitting line. Secondly, though our algorithm is apt for segmentation in mammograms, it can very well handle segmentation of other types of medical images. Thirdly, our segmentation based on Voronoi diagram can be extended to RGB images without converting them into gray scale. A comparison of advantages and disadvantages of various segmentation techniques is shown in Table V.

The features of an image are key to classification of the image to its respective class and pattern. In case of breast mammograms the features extracted will be useful in recognizing the class of the image (normal/abnormal) by training and testing using classifiers. The values obtained by different methods of segmentation shows variations in the feature values for same image. The feature extracted using segmentation based on our proposed method has an added advantage of reducing false positive result and is efficient for detecting infiltration areas from mammograms.

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