



Mammogram Image Segmentation using Fuzzy Markov Random Field

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Abstract -The breast cancer is the second largest cause of cancer death and the most frequently diagnosed cancer in women. Mammography is the best method for detecting breast cancer in the early stage. This work mainly focuses on the mammogram image segmentation using clustering techniques. The median filter is used for pre-processing of image and it is normally used to reduce noise in an image. Connected Component Labeling is used to remove the pectoral muscle. This paper proposed a new method Fuzzy Markov Random Field for mammogram image segmentation. It is cluster based method. Fuzzy Markov random field (FMRF) is a Markov Random Field in fuzzy space which handles fuzziness and randomness of data simultaneously. The result of the segmentation algorithms compared and analyzed using Mean Square Error (MSE) and Root Means Square Error (RMSE). It is observed that the proposed method produces better results than the existing methods. All the images used in this research have been taken from MIAS.

Keywords - Clustering, Image segmentation, Mammography, Median filter, Markov random field, Fuzzy Markov Random Field.

1. INTRODUCTION

Breast cancer is one of the most dangerous types of cancer among women in the world. It is proven that this dreadful disease ends the life of one among ten women. The World Health Organization's International estimated that more than 1, 50,000 women worldwide die of breast cancer in the year. In India, breast cancer accounts for 23% of all the female cancer death followed by cervical cancer which accounts to 27.5% in India. This disease occurs when the cells in the breast tissue turn to be abnormal. Cancer can be categorized as benign or malignant and this is determined by the shape of the mass. Usually, benign tumors are round or oval in shape and a malignant tumor can be observed with a partially rounded mass with a spike or an irregular outline. Benign tumors are non-cancerous whereas malignant tumors are cancerous in which, the cells grow abnormality.

Mammography is considered the most reliable method for early detection of breast cancer. Due to the high volume of mammograms to be read by the physicians, the accuracy rate tends to decrease and automatic reading of digital mammograms becomes highly desirable. It has been proven that the double reading of mammograms increased the accuracy but at high costs. That is why the computer aided diagnosis systems are necessary to assist the medical staff in achieving high efficiency and effectiveness.

Image segmentation is a major step in image processing and computer vision task. Segmentation refers to the process of partitioning a digital image into multiple segments or set of pixels in a way that each segment should be heterogeneous. The goal of segmentation is to simplify the representation of an image into different segments that are more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries in images. Image segmentation techniques can be classified into five main classes threshold based, cluster based, edge based, region based, and watershed-based segmentation (Armen Sahakyan & Hakop Sarukhanyan, 2012). This paper focuses on cluster based image segmentation.

Clustering is the task of grouping a set of objects together in such a way that objects in the same group are more similar to each other than to those in other groups. There are several methods to define quantity similarity between data points, among them Euclidian distance and Cosines distance are more common. Image segmentation is also considered as a clustering problem where the features describing each pixel correspond to a

pattern, and each image region corresponds to a cluster. The most popular methods are K-Means, FCM, spectral, ant colony, SOM, and Evolutionary clustering.

Fuzzy Markov Random Field is a Markov Random Field (MRF) in fuzzy space, which applies fuzzy random variables in the target process. Markov Random Field has become useful in several areas of image processing. The goal of MRF is to find the representation of the intensity distribution of an image. In FMRF, a data point only can take one value from label set L , which means that each data only should belong to one label of L . while, in FRMF, each data points belongs to all of the labels in L with different membership value for each one simultaneously. Estimating the optimal labeling of FMRF is similar to MRF, and both them are based on MAP framework (GokilaDeepa.G, 2012).

This paper aims to provide a cluster-based image segmentation framework based on FMRF model as in the figure 1. Fuzzy attribute of FMRF lead to boundary, noisy, and outlier data take the correct label, and somehow deal with uncertainty. Similar to the MRF, FMRF also need to initial labeling. This is critical stage in problem modeling and has an important role in final performance. This paper organized as follows: section 2 describes the preprocessing work. Section 3 discusses segmentation techniques. Section 4 discusses the experimental results and section 5 covers the conclusion.

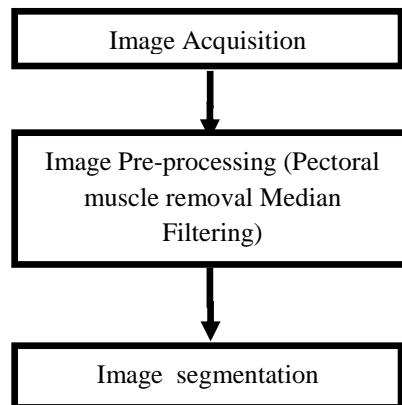


Figure 1. Overview for proposed model

2. RELATED WORK

Several researchers have introduced different approaches for segmenting the mammogram images. (Kamalakkannan. J 2016) presented various segmentation algorithms for mammogram images. (R. Subash Chandra Boss, 2013), presented mammogram image segmentation using fuzzy clustering. The fuzzy clustering data elements can belong to more than one cluster and associated with their membership values. (M. Suliga, 2008), proposed new pixel based clustering model for Markov Random Field applied to the analysis of digital mammograms. (Oliver, 2010), have reviewed some of the approaches of automatic detection and segmentation of masses in mammographic images, highlighting the key- points and main differences between the used strategies. (GokilaDeepa.G, 2012), proposed work utilizes Fuzzy C-Means clustering for segmentation and PSO for clear identification of clusters. The PSO and FCM is a new approach, using this we have successfully segmented the suspicious breast cancer masses in digital mammogram images. (K.Thangavel, 2012), presented an effective approach; relative dependency measure using the Rough Set Theory an attained 96% of segmentation accuracy rate (R.Vishnupriya, 2017), present the MR Image segmentation using Fuzzy Markov Random Field. The proposed algorithm are evaluated and compared with Fuzzy K-Means , Fuzzy C-Means and MRF methods both quantitatively and qualitatively to improve their efficiency. In this work we have used the fuzzy clustering approach for the segmentation of digital mammogram images. All the images used in this research have been taken from MIAS.

3. IMAGE ACQUISITION AND PRE-PROCESSING

3.1. Dataset

The Mammography Image Analysis Society (MIAS) which is an organization of UK research groups interested in the understanding of mammograms, has produced a digital mammography database (<ftp://peipa.essex.ac.uk>). The data used in this experiment was taken from MIAS. The database contains left and right breast images for 161 patients. Its quantity consists of 322 images, which belong to three types such as Normal, Benign and Malignant. There are 208 normal, 63 benign and 51 malignant (abnormal) images.

3.2. Pre-Processing

Image pre-processing techniques are necessary to improve the image quality by removing noise and unwanted background components of mammogram images. The main goal of the pre-processing is to improve the image quality to make it ready to further processing by removing or reducing the unrelated and surplus parts in the background of the mammogram images. Mammograms are medical images that complicated to interpret. Pre-processing methods use a small neighborhood of a pixel an input image to get a new brightness in the output image. Such pre-processing operations are called as a filtration. The aim of image is to visually enhance interesting features (like edges) or to suppress uninteresting features processing by removing or reducing the unrelated and surplus parts in the background of the image as in the figure 3.

3.3. Pectoral Muscle Removal

Pectoral muscles are the regions in mammograms that contain brightest pixels. These regions must be removed before detecting the tumor cells so must be removed before detecting the tumor cells so that mass detection can be done efficiently. Pectoral muscles lie on the left or right top corner depending on the view of the image. Connected component labeling is used to remove the pectoral muscle.

3.3.1. Connected Component Labeling

Connected component labeling is one of the most common operations in virtually all image processing applications. In machine vision most objects have surfaces. The points in a connected component form a candidate region to represent an object. The image object, which is the component, is separated from the background image on binary image. Then each component is labeled and displayed as output images. Points belonging to a surface project to spatially closed points. The notion of 'spatially closed' is captured by connected components in digital images (Oliver, 2010). Figure 2 shows the 4-neighborhood connected component.

In binary valued digital imaging, a pixel can either have a value of 1 when it's part of the pattern or 0 when it's part of the background, there is no grayscale level. It is assumed that pixels with value 1 are black while zero valued pixels are white).

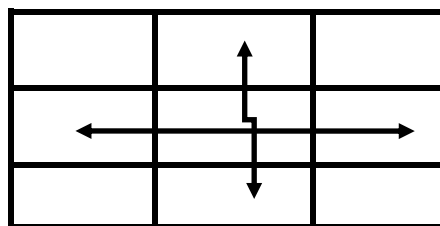


Figure 2. 4-neighborhood connected component

In order to identify objects in a digital pattern, we need to locate groups of black pixels that are “connected” to each other. In other words, the objects in given digital pattern are the connected components of that pattern. In general p_i and p_j in P , there exists P_1, \dots, P_j such that

- a) All pixels in the sequence are P , i.e, are black, and
- b) Every 2 pixels that are adjacent in the sequence are “neighbors”

Algorithm

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HISNCCLM (Im, th)
Im- original image. th- value
(1)  NIm  $\leftarrow$  Ims
(2)  chek(Im) left or right
(3)  If left
      Im  $\leftarrow$  fliplr(Im)
      End
(4)  hist  $\leftarrow$  hist(Im)
(5)  f Im  $\leftarrow$  medfilt2(Im)
(6)  bwIm  $\leftarrow$  im2bw( f Im, th )
(7)  l  $\leftarrow$  bwlabel(bwIm,4)
(8)  X  $\leftarrow$  find( l == 1 ) // breast region extraction
      X  $\leftarrow$  find( l ~= 1 ) // pectoral muscle removal
(9)  bw1 = f Im
(10) bw1( X ) = 0
      return( bw1 )
    
```

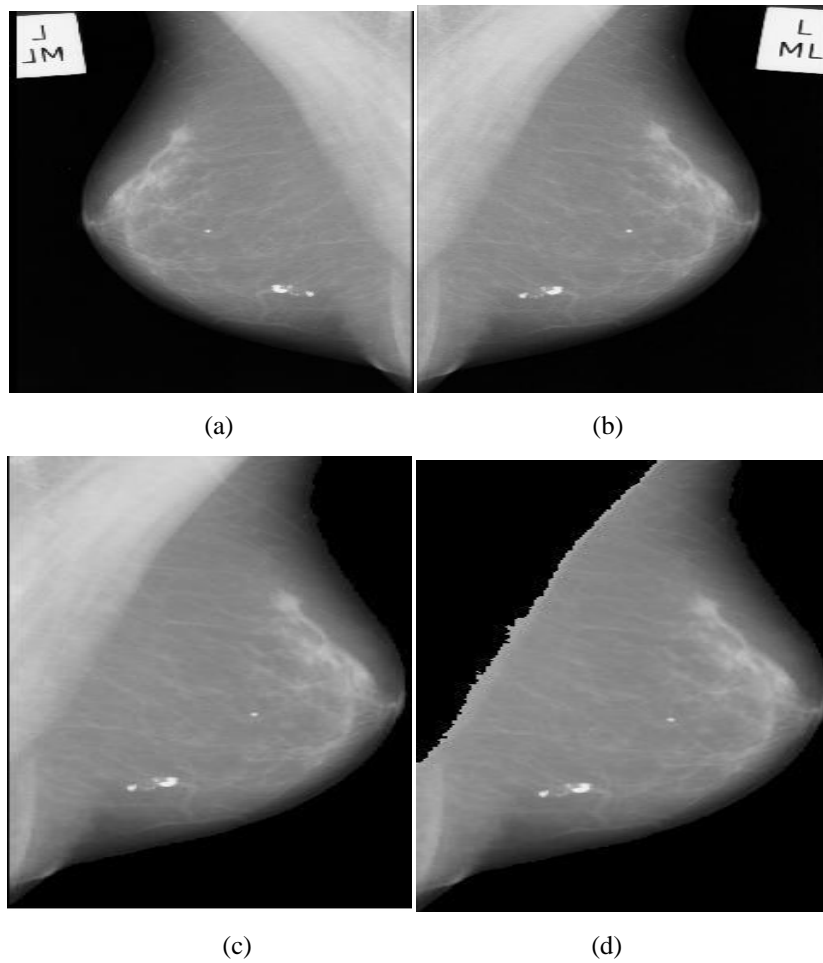


Figure 3. (a) Original image (b) Transformed image (c) Artifact removed image (d) Pectoral muscle removed image

3.3.2 Median Filter

Median Filters are Statistical non-linear filters that are described in the spatial domain. A median filter smoothens the images by utilizing the median of neighborhood. In median filtering, for each pixel, the values in the neighborhood window are organized according to the intensity and the middle value (Median) becomes the new value of the central pixel. i.e., each pixel is set to an 'average' of the pixel values of the neighborhood pixel rather than the mean. Then the median filter is given by the following expression

$$f(x, y) = \text{median}_{(s,t \in S_{xy})} \{g(s, t)\} \quad (1)$$

Following are some of the important features of the Median filter: It is a non-linear digital filtering technique. It is easy to change the size of the Median filter. Median filter for mammogram images to remove Quantum and Impulse noise. Its edge preserving nature makes it useful in many cases. The median value selected will be exactly equal to one of the existing brightness value so that no round-off error is involved when we work independently with integer brightness values comparing to the other filters (M. Suliga, 2008). The original image and the filtered image are shown in the figure 4 & 5.

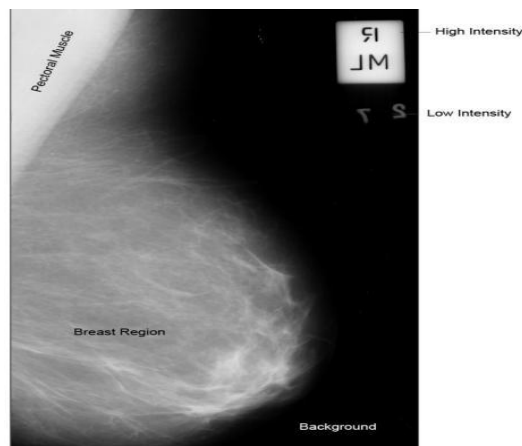


Figure 4. Shows the original image

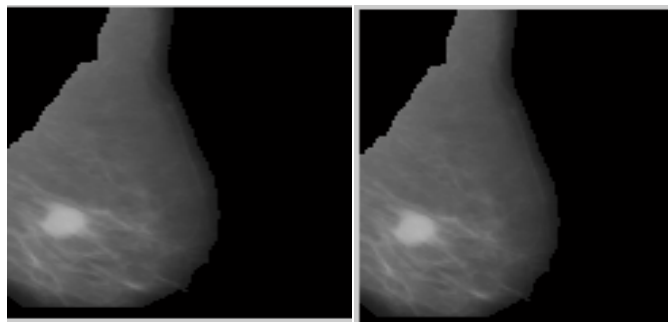


Figure 5. Filtered image

4. SEGMENTATION

The process of partitioning a digital image into multiple regions (set of pixels) is called image segmentation. The goal of segmentation is to simply the representation of an image into different segments that is more meaningful and easier to analyze. Mammogram image segmentation usually involves classifying mammograms into several distinct regions, including the breast border, the nipple and the pectoral muscle. Mammogram image segmentation techniques can be classified into five main classes threshold based, Cluster based, Edge based, Region based, and Watershed based segmentation (Subash Chandra Boss, 2013). In this work, we studied cluster

based segmentation using K-Means, Fuzzy C-Means (FCM) and proposed Fuzzy Markov Random Field (FMRF) based segmentation.

4. 1. K-Means

One of the most popular clustering methods is K-Means clustering algorithm. It classifies object to a pre-defined number of clusters, which is given by the user (assume K clusters). Each data point is assigned to the cluster with closest centroids. In this algorithm mostly Euclidean distance is used to find distance between data points and centroids (R. Subash Chandra Boss, Automatic Mammogram image Breast Region Extraction and Removal of Pectoral Muscle, 2013). The Euclidean distance between two multi-dimensional data points are shown in equation 2 $X = (x_1, x_2, x_3, \dots, x_m)$ and $Y = (y_1, y_2, y_3, \dots, y_m)$ is described as in the equation (2)

$$D(X, Y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2} \quad (2)$$

The K-Means method aims to minimize the sum of squared distances between all points and the cluster centre.

Algorithm 1: *K-Means*

Input: $D = \{d_1, d_2, d_3, \dots, d_n\}$ // set of n data points. K- Number of desired clusters.

Output: A set of K clusters.

Step-1 : Arbitrarily choose K data points from D as initial centroids;

Step-2 : Repeat,

Assign each point d_i to the cluster which has a closest centroid;

Calculate the new mean for each cluster;

Step-3 : Until convergence criteria is met.

4. 2. Fuzzy C-Means

Fuzzy C-Means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. In fuzzy clustering (also referred to as soft clustering), data elements can belong to more than one cluster, and associated with each element is a set of membership levels. Fuzzy clustering is a process of assigning these membership levels, and then using them to assign data elements to one or more clusters.

Algorithm 2: *Fuzzy C-Means*

Input: Dataset X of n objects with d features, value of K and Fuzzification value $m > 1$.

Output: Membership matrix U_{ij} for n objects and K clusters.

Step-1 : Randomly Initialize the membership matrix using this equation (3),

$$\sum_{j=1}^C \mu_j(x_i) = 1 \quad i = 1, 2, \dots, k \quad (3)$$

Step-2 : Calculate the Centroid using the equation (4),

$$C_j = \frac{\sum_i [\mu_j(x_i)]^m x_i}{\sum_i [\mu_j(x_i)]^m} \quad (4)$$

Step-3 : Calculate dissimilarity between the data points and Centroid using the Euclidean distance in the equation (5).

$$D_i = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \quad (5)$$

Step-4 : Update the New membership matrix using the equation (6),

$$\mu_j(x_i) = \frac{\left[\frac{1}{d_{ji}}\right]^{1/m-1}}{\sum_{k=1}^C \left[\frac{1}{d_{ki}}\right]^{1/m-1}} \quad (6)$$

Here m is a fuzzification parameter.

The range \mathbf{m} is always [1.25, 2]

Step -5: Go back to Step 2, unless the centroids are not changing.

4. 3. Fuzzy Markov Random Field

In fuzzy clustering (also referred to as soft clustering), data elements can belong to more than one cluster, and associated with each element is set of membership levels. These indicate the strength of the association between that data element and a particular cluster 1 and 4. Fuzzy clustering is a process of assigning these membership levels, and then using them to assign data elements to one or more clusters.

In the MRF model, a pixel can only take one value from a state space, which means each pixel must belong to one and only one region. Nevertheless a Fuzzy Markov Random Field (FMRF) model allows each pixel belonging to all regions simultaneously with different variables. Then each pixel has a vector (u_1, u_2, \dots, u_k) , with $u_1 + u_2 + \dots + u_k = 1$, and the value u_i , $i = 1, 2, \dots, k$ represents the likelihood that the pixel belongs to region i . if $u_i = 1$, the Fuzzy MRF becomes the pure MRF (GokilaDeepa.G, 2012).

4.3.1 Initial Labeling

The performance of FMRF model closely related to initial labeling step. Hence, the role of initial labeling in efficiency of results is obvious. Therefore, we perform the initial labeling by assigning to each pixel a class, to which centroid its gray level is the closest. After that initial segmentation is performed, membership value of each data (pixel) to all centers in range [0, 1] is calculated via equation (1). Then, we assign them as data membership vector to each correspond node in FMRF. Finally, energy minimization method uses the obtained vector for following optimization process.

$$w_{ij} = \frac{1}{\sum_{k=1}^c \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{2/m-1}} \quad (7)$$

In the equation (7) $X = \{x_1, x_2, \dots, x_n\}$ refer to data set X , $C = \{c_1, c_2, \dots, c_n\}$ is the set of cluster centers, w_{ij} defines membership value of data i for center j , and m determines the fuzziness of membership value (m should be set equal or greater than one). Higher value of m leading to smaller membership values, and in contrary $m=1$ results in membership values with {0, 1} which implies to crisp membership. Usually in most problems $m=2$ is assumed.

4.3.2 Energy Function Modeling

Energy minimization is particularly popular in medical image segmentation, where a function is first formulated to evaluate the goodness of segmentation for certain image, and the resulting segmentation of this image is given by minimizing such a function. In FMRF, likelihood energy determined based on membership value of each data to labels in label set L , which via equation (8) calculated.

$$V_F(y_i | x_i) = e^{-w_{y_i x_i}} \quad (8)$$

Which refer y_i to observed value of data i , x_i is the label of node i , and $w_{y_i x_i}$ presents degree of membership data y_i to label x_i , by using negative exponential, higher membership value results in lower energy and vice versa. This function checks that whether the two neighbor data (pixels) are in a same cluster or not. Typically, second order clique potential compiles with using model which can be defined as equation (9).

$$V_F(x_i, x'_i) = \begin{cases} -\beta, & (x_i = x'_i) \\ \beta, & (x_i \neq x'_i) \end{cases} \quad (9)$$

Which β is a constant penalty value in range [0, 1], and x_i, x'_i are labels of two neighboring nodes in FMRF. So as two nodes have same label, penalty would be $-\beta$, otherwise β be considered as penalty that two neighboring nodes which have different label. Clique potential forcing two similar neighbors have different label. Finally, energy function is defined as sum of the likelihood and second order energies, while presented in equation (10).

$$U_F(x|y) = \sum_{i \in S} V_F(y_i | x_i) + \sum_{i \in S} \sum_{N_i} V_F(x_i, x'_i) \quad (10)$$

 Algorithm 3: *Fuzzy Markov Random Field (FMRF)*

 Input: $S \rightarrow$ Mammogram digital image, $C \rightarrow$ No. of clusters

 Output: $SG \rightarrow$ Segment Group

 Step-1: Set $SG \rightarrow \{\}, X \rightarrow \{\}$

 Step-2: Find $X = \{X_1, X_2, \dots, X_M\}$ using

$$Possitivity : P(x) > 0, \forall x \in X$$

$$Markovianity : P(x_i | x_{N_i})$$

 $X \rightarrow$ family of random variables defined on the set S

 Which each random variable X_i takes a value x_i in a label set L

 Step-3: Randomly Initialize the membership matrix of X using the equation (11),

$$\sum_{j=1}^C \mu_j(x_i) = 1 \quad I = 1, 2, \dots, k \quad (11)$$

Step-4: Calculate the Centroid using equation,

$$C_j = \frac{\sum_i [\mu_j(x_i)]^m x_i}{\sum_i [\mu_j(x_i)]^m} \quad (12)$$

Step-5: Calculate dissimilarly between the data points and Centroid using the Euclidean distance (13).

$$D_i = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \quad (13)$$

Step-6: Update the New membership matrix using the equation (14),

$$\mu_j(x_i) = \frac{[\frac{1}{d_{ji}}]^{1/m-1}}{\sum_{k=1}^C [\frac{1}{d_{ki}}]^{1/m-1}} \quad (14)$$

 Here m is a fuzzification parameter.

Step-7: Go back to Step 2, unless the centroids are not changing.

Step-8: Apply energy minimization function (15) for assigning weight for each pixel and inference optimize clusters

$$U_F(x|y) = \sum_{i \in S} V_F(y_i | x_i) + \sum_{i \in S} \sum_{N_i} V_F(x_i, x'_i) \quad (15)$$

 Step-9: if $\mu_j(x_i) > 0.7$ $j = 1, 2, \dots, C$

$$SG\{j\} \leftarrow \mu_j(x_i)$$

 Step-10: Return SG

5. EVALUATION MEASURES

A segmentation evaluation measure is an efficient way to analyze the performance of existing and future algorithms. Segmentation evaluation metrics can be divided into boundary –based and region–based methods. Various performance parameters used for evaluation of image segmentation are as follows.

5.1. The Rand index (RI)

The Rand index or Rand measure is a measure of the similarity between two data clusters. The first metric evaluation is named Rand index and allows giving the accuracy of the segmentation comparing the Ground-Truth and the segmented image. This measure represents the closeness of the Ground Truth and the segmented image. The formula (16) allowing computing the distance is the following

$$R(GT, S) = 1 - \frac{n_{11} + n_{00}}{n(n-1)/2} \quad (16)$$

The distance tends to 0 if the segmented image is closed to the Ground Truth and tends to 1 when the difference between both images is important.

5.2. Global Consistency Error (GCE)

The Global Consistency Error (GCE) measures the extent to which one segmentation can be viewed as a refinement of the other. Segmentations which are related are considered to be consistent, since they could represent the same image segmented at different scales. Segmentation is simply a division of the pixels of an image into sets. The formula for GCE is as follows equation (17),

$$GCE = \frac{1}{n} \min\{\sum(S_1, S_2, P_i), \sum E(S_1, S_2, P_i)\} \quad (17)$$

5.3. Variation of Information (VI)

The Variation of Information (VI) metric defines the distance between two segmentations as average conditional entropy of one segmentation given the other, and thus measures the amount of randomness in one segmentation which cannot be explained by the other (N.Youssry, 2003). Suppose we have two clustering (a division of a set into several subsets) X and Y where is:

$$X = \{X_1, X_2, \dots, X_k\}, p_i = |X_i|/n \quad (18)$$

Then the variation of information (19) between two clustering

$$V_i(X:Y) = H(X) + H(Y) - 2I(X,Y) \quad (19)$$

Where, H(X) is entropy of X and I(X, Y) is mutual information between X and Y.

6. EXPERIMENTAL RESULTS

This section presents the results of experimental studies using fuzzy cluster based segmentation algorithm with the K-Means, FCM, and FMRF algorithms. All the data sets have been obtained from the images used for the experimental analysis are taken from the Mammogram Image Analysis Society (MIAS). It consists of 322 images, which belongs to three big categories: Normal, Benign and Malignant there are 209 normal images, 61 benign and 52 malignant. The images are clustered into five groups by FMRF algorithm, each groups is partition into one segment, the segmented image show in Table 2. The same features are used to cluster using K-Means and FCM with five groups each is partition into one segment, the segmented image shown in Table 2 and Table 3 describes the evaluation measures for various segmentation algorithms. The quality of segmentation result are measured using MSE and RMSE if the error value becomes low means that the better results.

6. 1. Quantative Measure

The image quality metrics such as Mean Square Error (MSE), Root Mean Square Error (RMSE), are used to evaluate the performance. The metrics are listed in table 1.

Table 1. Quantative Metrics

<i>Mertic</i>	<i>Formula</i>
MSE	$\frac{\sum_{m,n} [I_1(m,n) - I_2(m,n)]^2}{m * n}$
RMSE	$\sqrt{\frac{\sum_{m,n} [I_1(m,n) - I_2(m,n)]^2}{m * n}}$

Table 2. Results for proposed segmentation (FMRF) algorithm with other algorithms

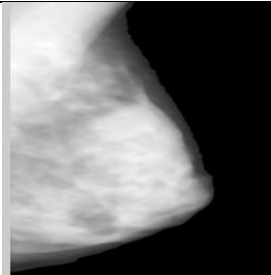
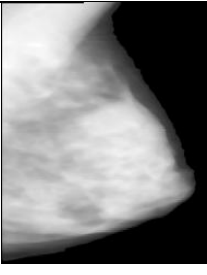
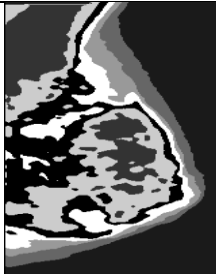
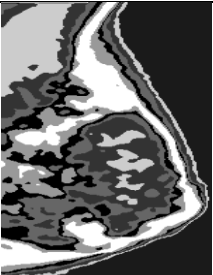
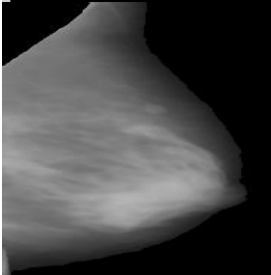
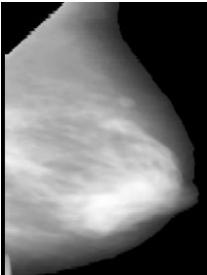
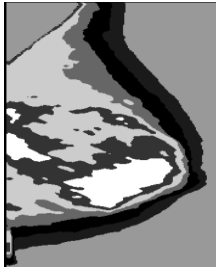
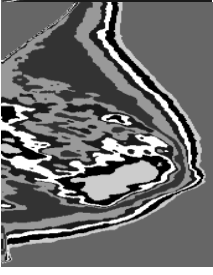
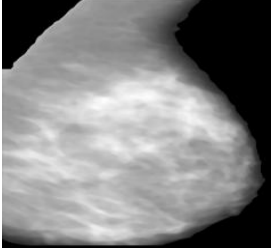
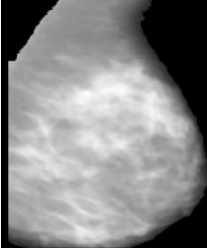
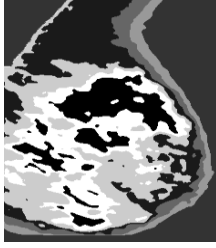
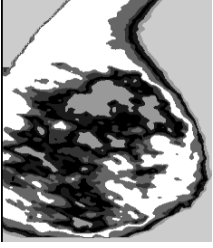
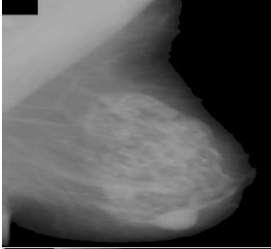
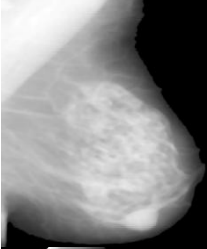
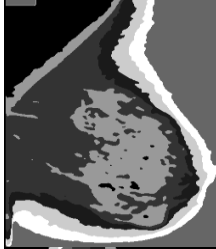
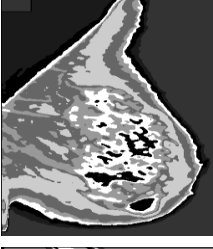
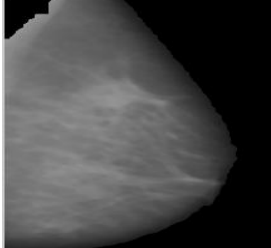
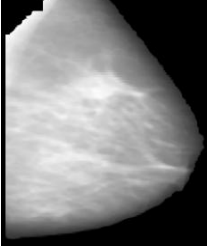


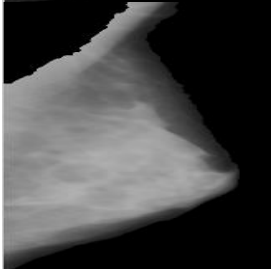
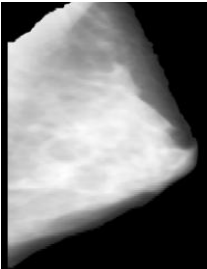
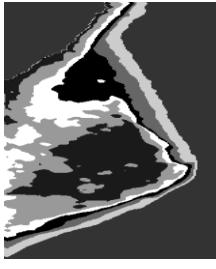

IMAGE ID	Original image	Segmented Image		
		K-Means	FCM	FMRF
mdb017				
mdb072				
mdb016				
mdb021				
mdb092				
mdb018				

Table 3. Performance of the proposed segmentation algorithm with other algorithms on various evaluation measures

Algorithm	MSE	RMSE
K-Means	9139.51	88.02
FCM	7532.45	85.69
FMRF	4253.35	64.52

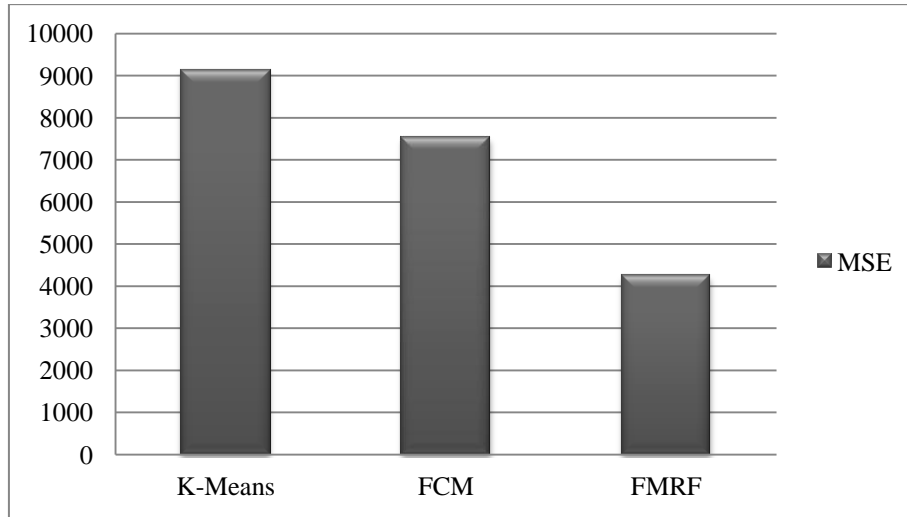


Figure 6. A comparison of MSE values for proposed algorithms and other clustering techniques.

Figure 6. shows the graphical representation of MSE Values for proposed algorithms and other clustering techniques.

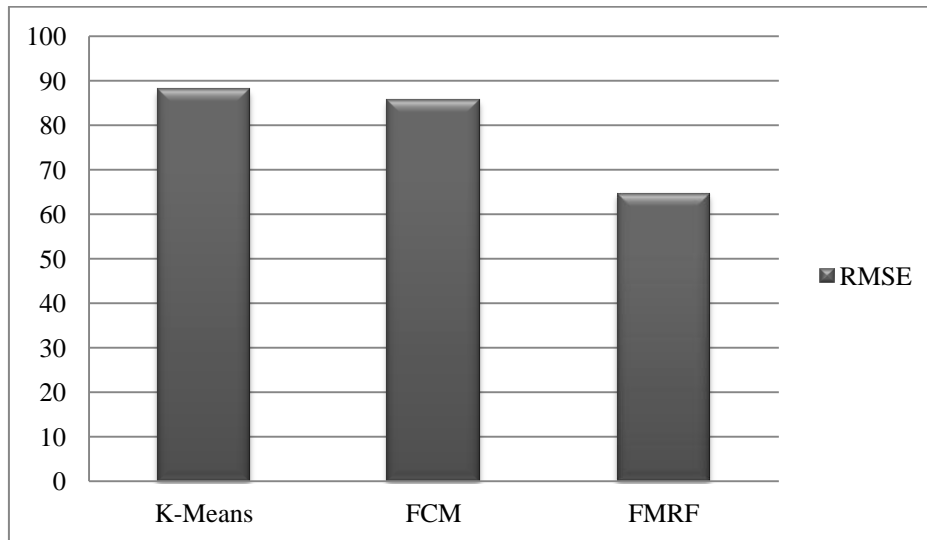


Figure 7. A comparison of RMSE values for proposed algorithms and other clustering techniques

Figure 7 shows the graphical representations of a comparison of RMS values for proposed algorithms and other clustering techniques.

Table 4. Evaluation measures for various segmentation algorithms

Algorithm	RI	GCE	VI
K means	0.9961	0.1819	1.3573
FCM	0.9766	0.0051	1.3292
FMRF	0.9796	4.3071	1.3728

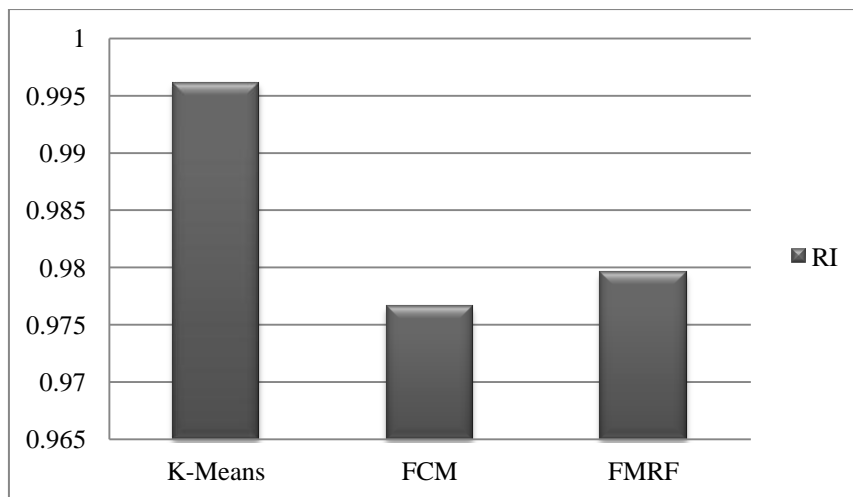


Figure 8. A comparison of Rand Index(RI) for proposed algorithms and other clustering techniques

Figure 8 shows a comparison of Rand Index (RI) for proposed algorithms and other clustering techniques.

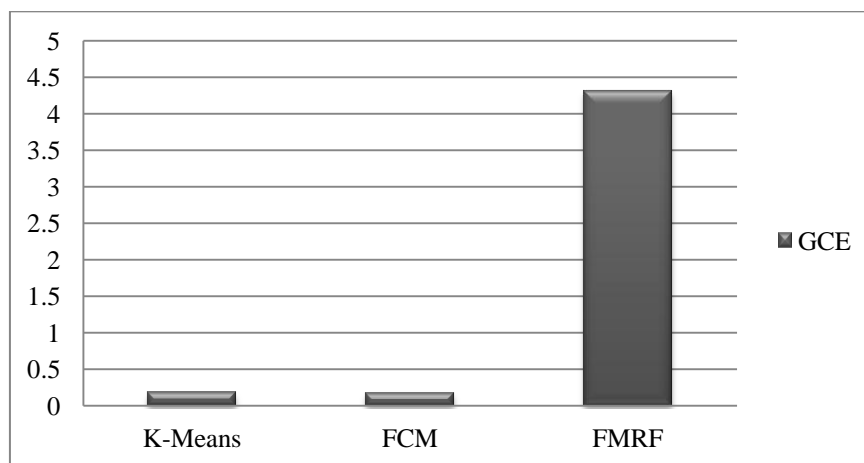


Figure 9. A comparison of GCE for proposed algorithms and other clustering techniques

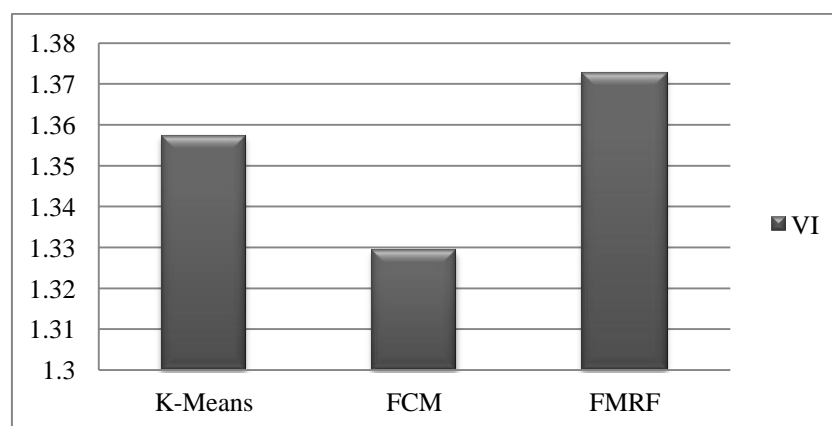


Figure 10. A comparison of VI for proposed algorithms and other clustering techniques

Figure 9 shows the graphical representations of a comparison of GCE for proposed algorithms and other clustering techniques. Figure 10 shows the graphical representation of a comparison of VI for proposed algorithms and other clustering techniques.

7. CONCLUSION

In this research, K-Means and Fuzzy C means clustering algorithms were studied and implemented. It was observed that the some parts of the tissues have been misclassified. The proposed segmentation algorithm (FMRF) was studied and implemented. It was compared with FCM and K-Means algorithm. In this paper, MSE and RMSE measures have been used to analyze the segmented images and to compare with benchmark algorithms. Further the resultant mammogram can be used for the detection of abnormalities in human breast such as micro-calcification, circumscribed lesions etc. This is the direction for further research.

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