CHAPTER 5

SEGMENTATION USING MODIFIED FUZZY POSSIBILISTIC C MEANS ALGORITHM WITH REPULSIONS

5.1. OVERVIEW

Segmentation is the process of partitioning a digital image into multiple segments. Image segmentation is used to locate objects and boundaries, lines and curves in images. The quality of segmentation depends on the image. It is essential to normalize the images used. There are two types of segmentations: top-down and bottom-up approaches. In top-down approach, contributions from object recognition are used for the segmentation process. For bottom-up approach, image brightness is used. A few practical applications of image segmentation are medical imaging, satellite imaging, face recognition, iris recognition, fingerprint recognition, traffic control systems, machine vision, and agricultural imaging.

Gafen et al (2003), analysed tissue characterisation classifiers for breast mammary carcinoma diagnosis based on Receiver Operating Characteristic (ROC) analysis. A fusion technique working on fractional diagnostic data is used. An algorithm to investigate the difference in shape symmetry between malignant and benign breast tumours is necessary.

5.2. SEGMENTATION IN ULTRASOUND IMAGES

The objective of segmentation in US image is to simplify and/or change the representation of the image into meaningful and easy process.
Parveen et al (2008), proposed to segment the breast tumors in ultrasound images. The computer-aided system evaluates tumors and distinguishes benign and malignant nodules. The results extracted for the different features are coherent with and assist in decision making process.

The preprocessed US image is intervened for the region of interest (ROI) selection by a human operator. Based on the ROI, the edges and boundaries are detected. Segmentation is performed in order to detect the occurrence of cancer regions in the ROI. The research uses a new segmentation algorithm called Modified Fuzzy Possibilistic C-Means (MFPCM) with Repulsion. The clustering technique includes the advantages of both Fuzzy Possibilistic Clustering Algorithm and C-Means clustering algorithm. The weighing factor is included in the clustering algorithm; increases the objective function. A repulsion term is introduced in the objective function to increase the intra cluster distance in the cluster and helps in better segmentation. The methodology is discussed in the Figure 5.1 as,

![Figure 5.1 Segmentation process](image-url)
Hilal et al (2009), aided the six step algorithm to identify and segment lesions in US images. The methodology uses radial intensity analysis followed by a uniform illumination constraint function to highlight the region of interest.

5.2.1. Edge Detection

In an image, an edge is a curve that follows a path of rapid change in image intensity. Edges are often associated with the boundaries of objects in a scene. Edge detection is used to identify the edges in an image. The edge function looks for intensity changing places in the image, using one of the criteria:

- The first derivative of the intensity is larger than threshold
- The second derivative of the intensity has a zero crossing

Canny edge detector is the primarily used detector for its robustness to reduce noise and its equal treatment of false positives and false negatives. The Canny edge method finds edges by looking for local maxima of the gradient of I. The gradient is calculated using the derivative of a Gaussian filter. The Canny method differs from the other edge-detection methods in that it uses two different thresholds, and includes the weak edges in the output only if connected to strong edges. This method is therefore less used than others and detects true weak edges.

5.2.2. Detection of Breast Boundaries

The isolation of the outermost body edges was performed by finding the edge pixels at the leftmost, rightmost, and topmost of the image. The boundary between the left and right breasts was taken to be the midpoint between the leftmost and rightmost boundaries. When all the boundaries are detected, the left and right breasts are isolated for further analysis. Ruoyu Du
et al (2009), suggested a sigma filter to change the neighbor pixels of targets. Comparison of results is done with FCM algorithm in visual evaluation and quantitative evaluation.

5.3. FUZZY POSSIBILISTIC C MEANS

Chen et al (2006), suggested a Fuzzy C Means (FCM) clustering in 3D MR images. Segmentation was done in six consecutive stages - Region Of Interest (ROI) selection by a human operator, Lesion enhancement within the selected ROI, Application of FCM on the enhanced ROI, Binarization of the lesion membership map, Connected component labeling and object selection and Hole-filling on the selected object.

The fuzzified version of the k-means algorithm is FCM. It is a clustering approach to allow a cluster of data to communicate to two or more clusters. Dunn in 1973 developed the technique and is modified by Bezdek in 1981 and is widely used in pattern recognition. The algorithm is an iterative clustering approach that brings out an optimal C-partition by minimizing the weights within group sum of squared error, objective function \( J_{FCM} \) is given in Equation (5.1),

\[
J_{FCM}(V, U, X) = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{m} d^2(X_j, v_i), \quad 1 < m < +\infty \quad (5.1)
\]

In the equation,

- \( X = \{x_1, x_2, ..., x_n\} \subseteq \mathbb{R}^p \) is the data set in the p-dimensional vector space \( \mathbb{R} \),
- \( p \) is the number of data items,
- \( c \) represents the number of clusters with \( 2 \leq c \leq n - 1 \),
- \( n \) represents the number of patterns in the dataset \( 1 < n < \infty \).
V = \{v_1, v_2, \ldots, v_c\} is the c centers or prototypes of the clusters,

v_i represents the p-dimension center of the cluster i,

d^2(x_j, v_i) represents a distance measure between object x_j and
cluster centre v_i.

U = \{\mu_{ij}\} represents a fuzzy partition matrix

\mu_{ij} = \mu_i(x_j) is the degree of membership of x_j in the i^{th} cluster

x_j is the j^{th} of p-dimensional measured data.

The fuzzy partition matrix satisfies the conditions by the
Equations (5.2) and (5.3),

\begin{align}
0 < \sum_{j=1}^{n} \mu_{ij} < n, \quad \forall \quad i \in \{1, \ldots, c\} \\
\sum_{i=1}^{c} \mu_{ij} = 1, \quad \forall \quad j \in \{1, \ldots, n\}
\end{align}

m is a weighing exponent parameter on each fuzzy membership and
establishes the amount of fuzziness of the resulting classification; it is a fixed
number greater than one. Under the constraint of U the objective function
J_{FCM} is minimized. Considering J_{FCM} with respect to \mu_{ij} and v_i and zeroing
them is a necessary but not sufficient conditions for J_{FCM} to be at its local
extrema, as in Equations (5.4) and (5.5),

\begin{align}
\mu_{ij} = \left[ \sum_{k=1}^{c} \frac{d^2(x_j, v_k)}{d^2(x_j, v_i)} \right]^{-1}, \quad 1 \leq i \leq c, \quad 1 \leq j \leq n. \tag{5.4}
\end{align}

where,

\begin{align}
v_i = \frac{\sum_{k=1}^{c} \mu_{ik}^m x_k}{\sum_{k=1}^{c} \mu_{ik}^m}, \quad 1 \leq i \leq c. \tag{5.5}
\end{align}
In a noisy environment, the memberships of FCM do not correspond to the degree of the belonging data and are inaccurate as it involves noises.

5.3.1. Fuzzy Possibilistic Clustering Algorithm

To recover the weakness of FCM, the constrained condition (5.3) of the Fuzzy C-partition is not taken into account. To obtain a possibilistic type of membership function and Possibilistic C Means (PCM) for unsupervised clustering is proposed. The component generated by the PCM belongs to a dense region in the data set; each cluster is independent of the other clusters in the PCM strategy. The Equation (5.6), $J$ is the objective function of the PCM,

$$J_{PCM}(V, U, X) = \sum_{d=1}^{c} \sum_{j=1}^{n} \mu_{ij}^m d^2(x_j, v_i) + \sum_{d=1}^{c} \eta_i \sum_{j=1}^{n}(1 - u_{ij})^m$$  \hspace{1cm} (5.6)

where, $\eta_i$ is the mobilization scale parameter at the $i^{th}$ cluster where membership value becomes 0.5, $u_{ij}$ represents the possibilistic typicality value of training sample $x_j$ belonging to the cluster $i$ are represented in Equations (5.7) and (5.8), $m \in [1, \infty]$ is a weighing factor the possibilistic parameter with $c$ represents the number of clusters with $2 \leq c \leq n - 1$ and $1 \leq k \leq n$ and $n$ is a real number between 1 to $\infty$.

$$\eta_i = \frac{\sum_{j=1}^{n} \mu_{ij}^m}{\sum_{j=1}^{n} \mu_{ij}^m}$$  \hspace{1cm} (5.7)

$$u_{ij} = \frac{1}{1 + \left[\frac{d^2(x_j, v_i)}{\eta_i} \right]^{m-1}}$$  \hspace{1cm} (5.8)

PCM is based on initialization of other cluster approaches. The clusters do not have mobility in PCM techniques, as each data point is classified as only one cluster at a time. A suitable initialization is necessary
for the algorithms to converge to nearly global minimum. The characteristic of both Fuzzy and Possibilistic C Means (FPCM) approach is incorporated. Memberships and typicalities are important factors for the correct feature of data substructure in clustering problem. The objective function $J_{FPCM}$ in the FPCM depends on both memberships and typicalities is represented in Equation (5.9),

$$J_{FPCM}(U, T, V) = \sum_{i=1}^{c} \sum_{j=1}^{n} (\mu_{ij}^m + t_{ij}^n) d^2(X_j, v_i)$$  \hspace{1cm} (5.9)$$

with the following constraints in Equations (5.10) and (5.11),

$$\sum_{i=1}^{c} \mu_{ij} = 1, \forall j \in \{1, \ldots, n\}$$  \hspace{1cm} (5.10)$$

$$\sum_{j=1}^{n} t_{ij} = 1, \forall i \in \{1, \ldots, c\}$$  \hspace{1cm} (5.11)$$

A solution to the objective function is obtained through an iterative process; the degrees of membership, typicality and the cluster centers are updated from Equations (5.10) and (5.11) with the Equations (5.12) to (5.14),

$$\mu_{ij} = \left[ \sum_{k=1}^{c} \left( \frac{d^2(X_j, v_k)}{d^2(X_j, v_k)} \right)^{2/(m-1)} \right]^{-1}, 1 \leq i \leq c, 1 \leq j \leq n. \hspace{1cm} (5.12)$$

$$t_{ij} = \left[ \sum_{k=1}^{n} \left( \frac{d^2(X_j, v_k)}{d^2(X_j, v_k)} \right)^{2/(n-1)} \right]^{-1}, 1 \leq i \leq c, 1 \leq j \leq n. \hspace{1cm} (5.13)$$

$$v_i = \frac{\sum_{k=1}^{c} (\mu_{ik}^m + t_{ik}^n) X_k}{\sum_{k=1}^{c} (\mu_{ik}^m + t_{ik}^n)}, 1 \leq i \leq c. \hspace{1cm} (5.14)$$

Possibilistic Fuzzy C Means (PFCM) constructs memberships and possibilities with the usual point prototypes or cluster centers for each cluster. Membership is described as relative typicality, the degree where the data fits
into the cluster in accordance with other clusters and is helpful in labeling the data point. Possibility is achieved as absolute typicality, determines the degree of belonging of data point to a cluster and decreases the noise consequence. Hybridization of PCM and FCM is the PFCM and avoids problems of PCM, FCM and FPCM. The noise sensitivity defect of FCM is solved by PFCM and this overcomes the coincident clusters problem of PCM excluding the estimation of centroids.

5.3.2. Modified Fuzzy Possibilistic C-Means

Objective function is necessary to enhance the quality of the clustering. The estimation of centroids is not determined accurately by the objective function as it is the inherent property. Mohammed Saad et al (2009), developed a Modified Fuzzy Possibilistic C-Means (MFPCM) based on the conventional FPCM to obtain better quality clustering results. The simulations resulted in a better clustering algorithm compared to FCM and FPCM methods.

The performance of FCM improves significantly to a prototype-driven-learning of parameter $\alpha$. Exponential separation strength between clusters is the base for learning process of $\alpha$ and is updated for all iterations. The parameter $\alpha$ is computed in Equation (5.15),

$$\alpha = \exp\left[-\min_{i \neq k} \frac{||x_j - y_k||^2}{\beta}\right] \quad 1 \leq k \leq n \tag{5.15}$$

In the above equation $\beta$ is a normalized term and is chosen as a sample variance. $\beta$ is given in Equation (5.16),

$$\beta = \frac{\sum_{j=1}^{n} ||x_j - \bar{x}||^2}{n} \text{ where } \bar{x} = \frac{\sum_{j=1}^{n} x_j}{n} \tag{5.16}$$
A new parameter is added to suppress the common value of $\alpha$ and replaces it with a weight parameter to each vector. Every point of the data set possesses a weight in relation to every cluster. This weight permits to have a better classification for a noisy data. The Equation (5.17) is used to calculate the weight,

$$w_{ji} = \exp \left[ -\frac{||x_j - \eta_i||^2}{\sum_{j=1}^{n}||x_j - \eta_i||^{c/n}} \right]$$

(5.17)

where $w_{ji}$ represents weight of the point $j$ in relation to the class $i$.

In order to alter the fuzzy and typical partition, $w_{ji}$ is used. The objective function is composed of two expressions:

- The first is the fuzzy function and uses a fuzziness weighting exponent
- The second is possibilistic function and uses a typical weighting exponent

The two coefficients in the objective function are used as exhibitors of membership and typicality. A new relation, enabling a more rapid decrease in the function and increase in the membership is used. The typicality tends towards 1 for a decrease in the degree and the typicality tends towards 0 for increases in the degree. This relation is to add weighting exponent as exhibitor of distance. The objective function of the MFPCM is in Equation (5.18),

$$J_{MFPCM} = \sum_{i=1}^{c} \sum_{j=1}^{n} \left( \mu_{ij}^m w_{ij}^m d^{2m}(x_j, v) + t_{ij}^n w_{ij}^n d^{2n}(x_j, v_i) \right)$$

(5.18)

$U = \{ \mu_{ij} \}$ represents a fuzzy partition matrix, as defined in Equation (5.19),
\[ \mu_{ij} = \left[ \sum_{k=1}^{c} \left( \frac{d^2(x_j, v_k)}{d^2(x_j, v_k)} \right)^{2m/(m-1)} \right]^{-1} \]  

(5.19)

\[ T = \{ t_{ij} \} \] represents a typical partition matrix, as defined in Equation (5.20),

\[ t_{ij} = \left[ \sum_{k=1}^{n} \left( \frac{d^2(x_j, v_k)}{d^2(x_j, v_k)} \right)^{2n/(n-1)} \right]^{-1} \]  

(5.20)

\[ V = \{ v_i \} \] represents c centers of the clusters, as defined in Equation (5.21),

\[ v_i = \frac{\sum_{k=1}^{n} (\mu_{ik} w_i^m t_{ik} w_i^n) x_i}{\sum_{k=1}^{n} (\mu_{ik} w_i^m t_{ik} w_i^n)} \quad 1 \leq k \leq n \]  

(5.21)

5.3.3. Penalized and Compensated Constraints based Modified Fuzzy Possibilistic C-Means

The Penalized and Compensated constraints are embedded in Modified Fuzzy Possibilistic C-Means (MFPCM) algorithm. The objective function of the FPCM is given in Equation (5.18). In the approach the penalized and compensated terms are added to the objective function of FPCM to construct the objective function of Penalized and Compensated Constraints based Modified Fuzzy Possibilistic C-Means (PCMFPCM). The penalized constraint is represented in Equation (5.22),

\[ \frac{1}{2} \nu \sum_{x=1}^{n} \sum_{i=1}^{c} (\mu_{x,i} m \alpha_i + t_{x,i} m \beta_i) \]  

(5.22)

where, \( \alpha \) and \( \beta \) is represented in Equations (5.23) and (5.24)

\[ \alpha_i = \frac{\sum_{x=1}^{n} \mu_{x,i}^m}{\sum_{x=1}^{n} \sum_{i=1}^{c} \mu_{x,i}^m}, \quad i = 1, 2, \ldots, c \]  

(5.23)
\[
\beta_x = \frac{\sum_{i=1}^{n} t_{x_i}^n}{\sum_{i=1}^{n} \sum_{j=1}^{n} t_{x_i}^n} \quad x = 1,2, ..., n \quad (5.24)
\]

\[\alpha_i \text{ is a proportional constant of class } i,\]
\[\beta_x \text{ is a proportional constant of training vector } z_x,\]
\[v (v \geq 0); \tau (\tau \geq 0) \text{ are constants.}\]

In the functions, \(\alpha_i\) and \(\beta_x\) are defined in equations above. Membership \(\mu_{x,i}\) and typicality \(t_{x,i}\) for the penals is represented in Equations (5.25) and (5.26),

\[
(\mu_{x,i})_p = \left( \sum_{x=1}^{c} \frac{(|| z_x - \sigma_{x} ||^2 - v in \alpha_i)^{1/(n-1)}}{(|| z_x - \sigma_{x} ||^2 - v in \alpha_i)^{1/(n-1)}} \right)^{-1} \quad x = 1, 2, ..., n, \quad i = 1, 2, ..., c. \quad (5.25)
\]

\[
(t_{x,i})_p = \left( \sum_{x=1}^{c} \frac{(|| z_x - \sigma_{x} ||^2 - v in \beta_i)^{1/(n-1)}}{(|| z_x - \sigma_{x} ||^2 - v in \beta_i)^{1/(n-1)}} \right)^{-1} \quad x = 1, 2, ..., n, \quad i = 1, 2, ..., c. \quad (5.26)
\]

In the previous expression \(\bar{w}_i = v_i = \frac{\sum_{x=1}^{n} (\mu_{x,i}^m + t_{x,i}) x_x}{\sum_{x=1}^{n} (\mu_{x,i}^m + t_{x,i})}, 1 \leq i \leq c\) is the centroid. The compensated constraints is represented in Equation (5.27)

\[
\frac{1}{2} \tau \sum_{x=1}^{n} \sum_{i=1}^{c} (\mu_{x,i}^m \tanh \alpha_i + t_{x,i}^n \tanh \beta_x)
\]

where membership \(\mu_{x,i}\) and typicality \(t_{x,i}\) for the compensation is in Equations (5.28) and (5.29)

\[
(\mu_{x,i})_c = \left( \sum_{x=1}^{c} \frac{(|| z_x - \sigma_{x} ||^2 - \tau \tanh (\alpha_i))^{1/(n-1)}}{(|| z_x - \sigma_{x} ||^2 - \tau \tanh (\alpha_i))^{1/(n-1)}} \right)^{-1} \quad x = 1, 2, ..., n, \quad i = 1, 2, ..., c, \quad (5.28)
\]

\[
(t_{x,i})_c = \left( \sum_{x=1}^{c} \frac{(|| z_x - \sigma_{x} ||^2 - \tau \tanh (\beta_i))^{1/(n-1)}}{(|| z_x - \sigma_{x} ||^2 - \tau \tanh (\beta_i))^{1/(n-1)}} \right)^{-1} \quad x = 1, 2, ..., n, \quad i = 1, 2, ..., c, \quad (5.29)
\]

To obtain an efficient clustering the penalization term is removed and the compensation term is added to the basic objective function of the
existing FPCM. This forms the objective function of PCFPCM and is given in Equation (5.30),

\[
J_{MFPCM} = \sum_{d=1}^{c} \sum_{j=1}^{n} (\mu_{ij}^d w_{ij}^d d^{2m}(x_i, v_j) + t_{ij}^d w_{ij}^d d^{2n}(x_i, v_j)) \\
- \frac{1}{2} \nu \sum_{x=1}^{n} \sum_{a=1}^{d} (\mu_{x,i}^a \ln \alpha_i + t_{x,i}^a \ln \beta_x) \\
+ \frac{1}{2} \nu \sum_{a=1}^{d} (\mu_{x,i}^a \tanh \alpha_i + t_{x,i}^a \tanh \beta_x) \\
(5.30)
\]

The centroid of \(i^{th}\) cluster is calculated as in Equation (5.21). The final objective function is presented in Equation (5.30).

5.4. CLUSTERING ENHANCEMENT USING REPULSIONS

In the clustering technique, the objective function is minimized only if all the centroids are identical and the typicality of a point to a cluster depends on the distance between the points to that cluster. The usage of repulsion aims to minimize the intra-cluster distances and maximizing the inter-cluster distances, without using the restriction and by adding a cluster repulsion term to the objective function \(J_{MFPCM}\) in Equation (5.31),

\[
J_{MFPCM} = \sum_{d=1}^{c} \sum_{j=1}^{n} (\mu_{ij}^d w_{ij}^d d^{2m}(x_i, v_j) + t_{ij}^d w_{ij}^d d^{2n}(x_i, v_j)) \\
- \frac{1}{2} \nu \sum_{a=1}^{d} \sum_{x=1}^{n} (\mu_{x,i}^a \ln \alpha_i + t_{x,i}^a \ln \beta_x) \\
+ \frac{1}{2} \nu \sum_{a=1}^{d} \sum_{x=1}^{d} (\mu_{x,i}^a \tanh \alpha_i + t_{x,i}^a \tanh \beta_x) \\
+ \sum_{d=1}^{c} \sum_{i=1}^{n} \eta_i \sum_{k=1}^{d} (1 - u_{ik}) + \gamma \sum_{d=1}^{c} \sum_{k=1}^{d} \frac{1}{d^2(v_{i}, v_{k})} \\
(5.31)
\]

where \(\gamma\) a weighting factor and \(u_{ik}\) is satisfied in Equation (5.32),

\[
u_{ik} \in [0, 1], \forall i \\
(5.32)
\]
The repulsion term is relevant if the clusters are close enough. The repulsion term becomes small until if it is compensated by the attraction of the clusters with distance growing. If the clusters are sufficiently spread out and the intercluster distance decreases, the attraction of the cluster is compensated only by the repulsion term. Minimization of objective function with respect to cluster prototypes leads to Equation (5.33),

\[
v_i = \frac{\sum_{j=1}^{n} u_{ij} x_j - \gamma \sum_{k \neq i} v_k d^2(v_k, v_i)}{\sum_{j=1}^{n} u_{ij} - \gamma \sum_{k \neq i} d^2(v_k, v_i)} \tag{5.33}
\]

Singularity occurs when one or more of the distances \(d^2(v_k, v_i) = 0\) at any iteration; \(v_i\) is not calculated and assign 0 to each nonsingular class and assign 1 to class \(i\), in the membership matrix \(U\). A repulsion term to minimize the objective function is given by the Equation (5.34),

\[
J_{MFPCM} = \sum_{i=1}^{c} \sum_{j=1}^{n} (\mu_{ij}^m w_{ji}^m d^2(x_j, v_i) + t_{ij}^n w_{ji}^n d^2(x_j, v_i)) - \frac{1}{2} \sum_{j=1}^{n} \sum_{i=1}^{c} (\mu_{ij}^m \ln \alpha_i + t_{ij, i}^n \ln \beta_{ij}) + \frac{1}{2} \sum_{j=1}^{n} \sum_{i=1}^{c} \mu_{ij}^m \ln \alpha_i + t_{ij}^n \tanh \beta_{ij}) + \sum_{j=1}^{n} \sum_{i=1}^{c} (1 - u_{ij})^m + \gamma \sum_{j=1}^{c} \sum_{k \neq i} \mu_{jk}^m e^{-d^2(v_k, v_i)} \tag{5.34}
\]

The weighting factor \(\gamma\) is used to balance the attraction and repulsion forces; minimizing the intra-distances inside clusters and maximizing the inter cluster distances.

The segmentation technique is applied to mammary gland image segmentation. Cheng et al. (2004), Cheng et al (2006), proposed segmentation using fuzzy logic on mammograms. The pixel values are the inputs of the clustering algorithm, and the pixels are clustered based on the optimum centers of clustering. The values of the pixels contained in the lesion are very low, the clusters of pixels with the less intensity are considered as the lesion-
like pixels. The mammary gland region is determined by the following formula as in Equation (5.35),

$$b_\omega(i, j) = \begin{cases} 
0, & g(i, j) \in C_1 \\
255, & otherwise
\end{cases}$$

(5.35)

where,

- g(i, j) - pixel in mammary gland region at the location (i, j)
- C$\_1$ - cluster with the lesser intensities.
- b$\_\omega$ - binary mammary gland image after segmentation.

After the mammary gland is segmented, the round-like regions are kept as the lesion-like regions and the others are rejected.

### 5.5. EXPERIMENTAL RESULTS

The experiment is conducted on the proposed computer-aided diagnosis systems with the help of real time 2D breast ultrasound images. The system is simulated using Matlab and tested for its performance by comparing with the Eliminating Particle Swarm Optimization algorithm given by Cheng et al (2010).

The input to the system is a speckle noise reduced (using Memetic ANFIS) and contrast enhanced (using fuzzy Hough Transformation) ultrasound image. To identify benign carcinoma, the preprocessed image is segmented using the MFPCM with repulsions algorithm. The segmentation algorithm clusters the ultrasound image according to its intensity and identifies the cancer affected regions. Chatterjee et al (2011), proposed a micro-calcification detection algorithm in two parts: segmentation of the mass and detection of micro-calcification within the mass.
The first process in the implementation is the selection of ROI. ROI type used is ‘polygon’. ROI portion to process is specified as a ‘statistical’ value for the ‘entire ROI’. The manually selected ROI polygon region uses the Canny edge detector in the Matlab. The first derivative of a Gaussian function to smooth the image is implemented and obtains the magnitude and orientation of the gradient for each pixel. A uniform threshold value 0.5 is applied to each image. The strongest edges in the image without removing the breast boundary are detected as in Figure 5.2.

![Image of edge detection](image)

**Figure 5.2 Feature selection**

Fuzzy C-Means is an iterative clustering technique applied to the edge detected image. A weighing exponent parameter value 0.5 is applied on each fuzzy membership and establishes the amount of fuzziness of the resulting classification, Figure 5.3.
Figure 5.3 Fuzzy clustering

The objective function values and its probability density function graph in Figures 5.4 to 5.6 shows the segmentation result on application of MFPCM.

Figure 5.4 Objective function values for MFPCM clustering
Figure 5.5 Probability Density Function for MFPCM

Figure 5.6 Segmentation on application of enhanced MFPCM
The intensity values of the pixel contained in the lesion is very low, the cluster of pixels with lesser intensities is considered as the lesion-like pixels. The mammary gland region is segmented as in Figure 5.7,

![Segmented Cancer Image](image)

**Figure 5.7** Segmented lesion using MFPCM with repulsions

Maleke et al (2009), suggested the initial feasibility of the Harmonic Motion Imaging for Focused Ultrasound (HMIFU) for thermal ablation generation and monitoring is shown in a transgenic mouse model of breast cancer. The HMIFU is used as a guidance tool for visualizing the targeted region (ROI) and monitoring the relative tissue stiffness change during thermal treatment so that the treatment is performed in both cost and time efficient manner.

Tables 5.1 to 5.3, Figures 5.8 to 5.10 represent the resulted accuracy, standard deviation and PSNR for segmentation of the ultrasound image used. The EPSO algorithm searches the optimum solution by eliminating the “weaker” particles to speed up the computation. The fitness function of each particle is evaluated by comparing the personal best of each particle in the new swarm, S(t+1), with its current fitness value and set the current primary population, P(t), to better one. From the data, it is observed
that the proposed segmentation algorithm results in better accuracy for segmentation when compared to the conventional technique.

Table 5.1 Segmentation accuracy comparison using modified fuzzy possibilistic C means with repulsion and eliminating particle swarm optimization

<table>
<thead>
<tr>
<th>Ultrasound Image</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>EPSO</td>
</tr>
<tr>
<td>1</td>
<td>97.31</td>
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<td>9</td>
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<tr>
<td>10</td>
<td>98.75</td>
</tr>
</tbody>
</table>

Figure 5.8 Comparison of segmentation accuracy using EPSO and MFPCM
From the data, it is observed that the proposed segmentation algorithm results in lesser standard deviation for segmentation in comparison to the conventional technique.

Table 5.2  Comparison of segmentation standard deviation using modified fuzzy possibilistic C means with repulsion and eliminating particle swarm optimization

<table>
<thead>
<tr>
<th>Ultrasound Image</th>
<th>Standard Deviation</th>
<th></th>
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Figure 5.9  Comparison of segmentation standard deviation using EPSO and MFPCM
Table 5.3  Comparison of peak signal to noise ratio using modified fuzzy possibilistic C means with repulsion and eliminating particle swarm optimization

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Figure 5.10  Comparison of segmentation peak signal to noise ratio using MFPCM and EPSO
Figure 5.11 represents the results of the comparison of both methods. This suggests that the proposed technique results in better segmentation and visibly detects the benign carcinoma and aids in computer-aided detection process.

![Figure 5.11 Segmentation comparisons of EPSO and MFPCM](image)

**Figure 5.11 Segmentation comparisons of EPSO and MFPCM**

5.6. **INFERENCES**

This chapter presents ultrasound image segmentation based on Modified Fuzzy Possibilistic C Means algorithm with repulsion. A preprocessed and contrast-enhanced image is the input to the system. The region of interest is chosen manually from the selected image to diagnose in both cost and time-efficient manner. The lesion is identified from the ROI using Modified Fuzzy Possibilistic C Means Clustering. The repulsion factor is used to increase the intra-cluster distance by finding the optimum centroid of the cluster. The algorithm is tested for its performance by comparing with the Eliminating Particle Swarm Optimization algorithm. The system sufficiently identifies carcinoma in its early stages (benign) and helps in computer-aided detection process.