CHAPTER 5

IMAGE ENHANCEMENT USING DENOISING

5.1 INTRODUCTION

Significant work has been published on the post-processing of compressed images. Most existing post-processing methods are designed to reduce (or to attenuate) the blocking artifacts caused by block discrete cosine transforms based (DCT-based) coding algorithms. Enhancement of compressed images has also been viewed as a restoration problem.

5.2 EXISTING TECHNIQUES

5.2.1 General Steps in Mammographic Lesion Detection

Global methods:

Texture analysis [43,95] allows us to segment the image and classify the segmented regions. These regions can create parameters for a forthcoming method. The segmentation (or region of interest localization) of the mammograms consists of three parts: preprocessing, “coarse” segmentation and “fine” segmentation. Preprocessing is used to take out the true breast region from the image using thresholding [41] and median filtering. Additional algorithms are working only on the extracted region. The second step (“coarse” segmentation) calculates various texture parameters (co-occurrence matrix [96], gray level run length [40], grey level differences [40] and histogram features [40] in a particular window to create the feature vector. The feature vector is accepted to a set of decision trees [97], which will classify the actual image segment (in which the feature vector is calculated). The decision trees are automatically produced from a set of training images. These training images contain a mass (or lesion) and some surrounding background tissue. The image is segmented using all the decision trees. The outcome is a vote board where each image segment can have a vote value between zero and the number of the classifying trees. This vote board is post processed to create a binary mask that
will cover regions of interests (suspected locations of lesions). It is treated as an image and adaptive filtering is applied to locate the most suspicious regions. The “fine” segmentation step uses a multiresolution Markov random field [30,39] to improve the preliminary segmentation provided by the “coarse” segmentation.

5.2.2 LOCAL METHODS

Another segmentation is performed on the patches using a combination of dual binarization, Bèzier histograms [31] and a modification of the radial gradient index method [64] to obtain a black-and-white mask. After receiving the mask of the lesion candidate, several parameters are considered. Many of them refer to the shape of the object [31], compactness, others refer to the texture of the object and its surroundings e.g. average brightness of the masked region, average intensity of the background, the proportion of these two numbers; and the average variance of the masked and unmasked regions. Based on these parameters, it can be determined whether the patch contains a true lesion or not. Presently human experts calculate the parameters, but the improvement of an automatic clustering module is in progress.

In this work, two automatic mammographic lesion detection algorithms namely Fuzzy C means Clustering and Otsu thresholding are compared with the proposed Active Contour model based algorithm.

5.2.3 FUZZY C-MEANS CLUSTERING

Fuzzy C-means Clustering (FCM), also known as Fuzzy ISODATA employs fuzzy partitioning such that a data point can belong to all groups with different membership grades between 0 and 1. FCM is an iterative algorithm. The objective of FCM is to find cluster centers (centroids) that minimize a dissimilarity function.
To accommodate the introduction of fuzzy partitioning, the membership matrix (U) is randomly initialized according to equation 5.1

$$\sum_{i=1}^{c} u_{ij} = 1, \forall j = 1,\ldots,n$$  \hspace{1cm} (5.1)

The dissimilarity function which is used in FCM is given by Equation 5.2

$$J(U, c_1, c_2,\ldots,c_c) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m d_{ij}^2$$  \hspace{1cm} (5.2)

$u_{ij}$ is between 0 and 1,

$c_i$ is the centroid of cluster $i$,

$d_{ij}$ is the Euclidian distance between $i_{th}$ centroid ($c_i$) and $j_{th}$ data point,

$m \in [1,\infty]$ is a weighting exponent.

To reach a minimum of dissimilarity function there are two conditions. These are given in equations 5.3 and 5.4

$$c_i = \frac{\sum_{j=1}^{n} u_{ij}^m x_j}{\sum_{j=1}^{n} u_{ij}^m}$$  \hspace{1cm} (5.3)

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}}\right)^{2/(m-1)}}$$  \hspace{1cm} (5.4)

By iteratively updating the cluster centers and the membership grades for each data point, FCM moves the cluster centers to the "right" location within a data set.
FCM does not ensure that it converges to an optimal solution because cluster centers (centroids) are initialized using $U$ that is randomly initialized (equation 5.3).

### 5.2.4 OTSU THRESHOLDING

Otsu’s method [64] chooses the optimal thresholds by maximizing the inter-class variance with an exhaustive search. It also chooses the threshold to minimize the intra class variance of the threshold black and white pixels.

This method is based on selecting the lowest point between two classes (peaks).

Frequency and Mean value are given by equations (5.5) and (5.6)

Frequency: $\omega = \sum_{i=0}^{r} p(i)$ \quad $P(i) = n_i / n$ \quad N: total pixels number \quad (5.5)

Mean: $\mu = \sum_{i=0}^{r} i = \frac{P(i)}{\omega}$ \quad $n_i$: number of pixels in level $i$ \quad (5.6)

Analysis of variance (variance = square of standard deviation) is given by equation (5.7)

Total variance: $\delta_i^2 = \sum_{i=0}^{r} (i = \mu)^2 P(i)$ \quad (5.7)

Between-classes variance ($\delta_b^2$) is given by the variation of the mean values for each class from the overall intensity mean of all pixels as in equation (5.8).

$$\delta_b^2 = \omega_0 (\mu_0 - \mu_t)^2 + \omega_1 (\mu_1 - \mu_t)^2,$$ \quad (5.8)

Substituting $\mu_t = \omega_0 \mu_0 + \omega_1 \mu_1$ in equation (5.8), equation (5.9) modifies to

$$\delta_b^2 = \omega_0 \omega_1 (\mu_1 - \mu_0)^2$$ \quad (5.9)
where $\omega_0, \omega_1, \mu_0, \mu_1$ stands for the frequencies and mean values of two classes, respectively.

The criterion function involves inter-classes variance to the total variance which is defined by equation (5.10)

$$\eta = \frac{\partial^2_b}{\partial^2_1}$$

(5.10)

All possible thresholds are evaluated in this way, and the one that maximizes $\eta$ is chosen as the optimal threshold

5.3 ACTIVE CONTOUR MODEL

The snake is the simplest form of active contours and the basic concept of this thesis. A snake is a contour that can be described as a function $v : [0,1] \rightarrow \mathbb{R}^2$ with some boundary conditions if required by the situation. The contour is placed on an image $f : \mathbb{R} \rightarrow \mathbb{R}^2$, and it moves towards an optimal position and shape by minimizing its own energy.

Fitting active contours to shapes in images is an interactive process. The operator must suggest an initial contour, which is quite close to the proposed shape. The contour will then be attracted to features in the image extracted by creating an attractor image.

5.3.1 OPEN AND CLOSED CONTOURS

The contour can be either a closed or an open curve. If the contour is open, one should take care to modify the contour definition of its energy so that the end-points will not move in the same way as the other points (avoiding the contour dragging itself into itself and vanishing).
5.3.2 THE ENERGY OF THE CONTOUR

The energy depends on the shape of the contour (internal energy) and on its positioning on the image according to equation (5.11)

\[ E(v, f) = E_{\text{image}}(v, f) + E_{\text{int}}(v) \]  

(5.11)

These energies influence all points along the contour with internal forces and an image force. When all forces are balanced, the total energy is at a minimum.

5.3.3 INTERNAL ENERGY

The internal energy of the contour depends on the shape of the contour and the parameter functions \( \alpha_s \) and \( \beta_s \) and is defined by equation (5.12)

\[ E_{\text{int}} = \int (\alpha(s)|v(s)|^2 + \beta(s)|v(s)|^2) ds \]  

(5.12)

The first term \(|v(s)|^2\), will have larger values if there is a large gap between successive points on the contour and minimizing it will minimize the total length of the contour1. The second term \(|v(s)|^2\), will be larger where the contour is bending and requires the contour to be as smooth as possible. These terms are weighted by parameter functions, and so \( \alpha_s \) determines the elasticity of the contour, and \( \beta_s \) determines the rigidity. If \( \alpha_s \) equals zero at some points then discontinuities are allowed there, and where \( \beta(s) \) equals zero, discontinuous curvature such as corners are allowed. To simplify, the parameter-functions will henceforth be regarded as constants.
5.3.4 IMAGE ENERGY

The image energy depends on how the contour is positioned on an attractor image, and it is defined as shown in equation (5.13)

$$E_{image} = -\int p(v(s), f)ds$$

(5.13)

and uses an attractor image given by equation (5.14)

$$p(x, f) = |\nabla f(x)|^2$$

(5.14)

This attractor image makes the contour draw to edges in the original image.

5.3.5 MINIMIZING THE ENERGY

Minimizing the energy (5.11) is equivalent to solving the corresponding Euler-Lagrange-equation (5.15)

$$\alpha v^m - Bv^{(4)} = -\nabla p(v, f)$$

(5.15)

which simply means that the internal forces shall balance the image forces

$$\alpha v^m - \beta v^{(4)}$$

In practice one does not study the contour at all points. As an alternative, the contour is represented by a vector $\overline{v}$ of control point’s $v_j$. The control points must not be separated by more than a few pixels to prevent the contour from bypassing attractive but small areas in the image. It is the purpose of the elasticity force to keep the control points equidistant. In the control points $v_j$ the derivatives in (5.15) can be approximated by finite differences [39], which are given by equations (5.16) and (5.17)
\[ v_j^{(m)} = v_{j-1} - 2v_j + v_{j+1} \quad (5.16) \]

\[ v_j^{(4)} = v_{j-2} - 4v_{j-1} + 6v_j - 4v_{j+1} + v_{j+2} \quad (5.17) \]

Using these expressions equation (5.15) can be written as

\[ A\tilde{v} + \nabla p(\tilde{v}, f) = 0 \]

Where \( A \) is the matrix given by (5.16) and (5.17) and insertion of \( A \) contour can then be calculated with iterations according to Euler’s method [90] as shown in equation (5.18)

\[ (I + A)\tilde{v}_{k+1} = \tilde{v}_k + \nabla p(\tilde{v}_k, f) \quad (5.18) \]

Where \( \tilde{v}_0 \) is the set of originally suggested control points. One iteration makes each control point move so far in the direction of the image force so that it is balanced by the resulting internal forces.

Active contours “snakes” can be used to segment objects automatically. The fundamental idea is the evolution of a curve or curves subject to constraints from the input data. The curve should progress until its boundary segments the object of interest. This framework has been used successfully by Kass et al. [40,98] to extract boundaries and edges. One possible difficulty with this approach is that the topology of the region to be segmented must be known in advance.

The propagating curve is modeled as a specific level set of a higher dimensional exterior. It is a general practice to model this surface as a function of time. So as time progresses, the surface can alter to take on the desired shape.
5.4 MATHEMATICAL FORMULATION OF LEVEL SETS

Let $\Omega$ be a bounded open subset of $\mathbb{R}^2$, with $d\Omega$ as its boundary. Then a two dimensional image $u_0$ can be defined as $u_0 : \Omega \to \mathbb{R}$. In this case, $\Omega$ is just a fixed rectangular grid. Now consider the evolving curve $C$ in $\Omega$, as the boundary of an open subset $\omega$ of $\Omega$. In other words $\omega \subseteq C$, and $C$ is the boundary of $\omega$ ($C = d\omega$).

The main idea is to embed this propagating curve as the zero level set of a higher dimensional function $\phi$. The function is defined as follows as shown in equation (5.19)

$$\phi(x, y, t = 0) = \pm d$$  \hspace{1cm} (5.19)

where $d$ is the distance from $(x,y)$ to $d\omega$ at $t = 0$, and the plus (minus) sign is chosen if the point $(x,y)$ is outside (inside) the subset $\omega$.

Now, the goal is to produce an equation for the evolution of the curve. Developing the curve in the direction of its normal amounts to solving the partial differential equation as given by equation (5.20)

$$\frac{\partial \phi}{\partial t} = F |\nabla \phi|, \phi(x, y, 0) = \phi_0 (x, y)$$  \hspace{1cm} (5.20)

Where $\{(x,y), \phi_0(x,y) = 0\}$ defines the primary contour, and $F$ is the speed of proliferation. For assured forms of the speed function $F$, this reduces to a standard Hamilton-Jacobi equation. There are numerous major advantages to this formulation. The first is that $\phi(x,y,t)$ always remains a function as long as $F$ is smooth. As the surface $\phi$ evolves, the curve $C$ may crack, combine and change topology.
Another advantage is that the geometric properties of the curve are easily determined from a particular level set of the surface \( \phi \). For instance, the normal vector for any point on the curve \( C \) is given by equation (5.21)

\[
\vec{n} = \nabla \phi
\]  

(5.21)

and the curvature \( K \) is obtained from the divergence of the gradient of the unit normal vector to the front as shown in equation (5.22)

\[
K = \text{div} \left( \frac{\phi_{X} \phi_{S}^{2} - 2 \phi_{X} \phi_{S} \phi_{S} + \phi_{S} \phi_{S}^{2}}{\left( \phi_{X}^{2} + \phi_{S}^{2} \right)^{3/2}} \right)
\]  

(5.22)

Another advantage is that one is able to evolve curves in dimensions higher than two. The above formulae can be simply extended to deal with high dimensions. This is helpful in propagating a curve to segment volume data.

### 5.5 ACTIVE CONTOURS WITHOUT EDGES

As given earlier the curve \( C \) can be viewed as the boundary of an open subset \( \omega \) of \( \Omega \) (i.e. \( C = \partial \omega \)). The region \( \omega \) is denoted by inside(\( C \)) and the region \( \Omega - \omega \) by outside(\( C \)). Rather than basing the model on an edge-stopping function, the evolution of the curve is halted with a energy minimization approach.

A simple case is considered where the image \( u_0 \) is formed by two regions of piecewise constant intensity. The intensity values are denoted by \( u_{00} \) and \( u_{01} \). Furthermore, it is assumed that the object to be detected has a region whose boundary is \( C_0 \) and intensity \( u_{01} \). Then inside (\( C_0 \)), the intensity of \( u_0 \) is approximately \( u_{1,0} \), whereas outside(\( C_0 \)) the intensity of \( u_0 \) is approximately \( u_{0,0} \). Then the fitting term is considered as shown in equation (5.23)
\[ F_1(c) + F_2(c) = \int_{\text{inside}(c)} |u_0(x, y) - c_1|^2 \, dx \, dy + \int_{\text{outside}(c)} |u_0(x, y) - c_2|^2 \, dx \, dy \]  \quad (5.23)

where C is a curve, and the constants \( c_1, c_2 \) are the averages of \( u_0 \) inside and outside of C respectively. From the figure 5.1, if the curve C is outside the object, then \( F_1(C) > 0, F_2(C) \approx 0 \). If the curve is inside the object, then \( F_1(C) \approx 0, F_2(C) > 0 \). If the curve is both inside and outside the object, then \( F_1(C) > 0; F_2(C) > 0 \). However, if the curve C is exactly on the object boundary \( C_0 \), then \( F_1(C) \approx 0, F_2(C) \approx 0 \), and the fitting term is minimized.

Some regularization terms are added as in the Mumford-Shah segmentation model \([99]\). Therefore attempts are made to minimize the length of the curve and the area of the region inside the curve. So the energy function \( E \) is given by equation (5.24)

\[
E(C, c_1, c_2) = \mu \cdot \text{Length}(c) + \nu \cdot \text{Area(inside}(c)) + \lambda_1 \int_{\text{inside}(c)} |u_0(x, y) - c_1|^2 \, dx \, dy \\
+ \lambda_2 \int_{\text{outside}(c)} |u_0(x, y) - c_2|^2 \, dx \, dy 
\]  \quad (5.24)

where \( \mu \geq 0, \nu \geq 0, \lambda_1 > 0, \lambda_2 > 0 \) are fixed parameters. So the goal is to find \( C, c_1; c_2 \) such that \( E(C, c_1, c_2) \) is minimized.

Mathematically, it is to solve

\[
\sum_{j=1}^{c} u_j = 1, \forall j = 1, \ldots, n
\]
\begin{align*}
  &F_1(C) > 0, F_2(C) = 0 \\
  &F_1(C) = 0, F_2(C) > 0 \\
  \text{Fitting Term} > 0 & \\

text}

\text{Figure 5.1 Possible cases in position of the curve when Fitting Term} \ > \ 0.

\begin{align*}
  &F_1(C) > 0, F_2(C) > 0 \\
  &F_1(C) = 0, F_2(C) = 0 \\
  \text{Fitting Term} > 0 & \\
  \text{Fitting Term} \approx 0
\end{align*}

\text{Figure 5.2 Possible cases in position of the curve when Fitting Term} \ > 0 \text{ and} \ = 0.

This problem can be formulated using level sets as follows. The developing curve \( C \) can be represented by the zero level set of the signed distance function \( \phi \) as in (5.19). So the unknown variable \( C \) is replaced by \( \phi \). Now the Heaviside function \( H \) is considered, and the Dirac is measured as shown in equation (5.25)

\[ H(z) = \begin{cases} 
  1 & \text{if } z \geq 0 \\
  0 & \text{if } z < 0
\end{cases} \quad \partial(z) = \frac{d}{dz} H(z) \]  

(5.25)

The length of \( \phi = 0 \) and the area of the region inside(\( \phi = 0 \)) can be rewritten using these functions. The Heaviside function is positive inside the curve and zero.
elsewhere, so the area of the region is just the central of the Heaviside function of $\phi$. The gradient of the Heaviside function defines the curve, so integrating over this region gives the length of the curve.

Mathematically as given in equation (5.26)

$$\text{Area}(\phi = 0) = \int_{\Omega} H(\phi(x, y)) \, dx \, dy$$

$$\text{Length}(\phi = 0) = \int_{\Omega} |\nabla H(\phi(x, y))| \, dx \, dy$$

$$= \int_{\Omega} \partial(\phi(x, y)) |\nabla \phi(x, y)| \, dx \, dy \quad (5.26)$$

Similarly, the previous energy equations can be rewritten so that they are defined over the entire domain rather than separated into inside(C) = $\phi > 0$ and outside(C) = $\phi < 0$: as shown in equation (5.27)

$$\int_{\phi<0} |u_0(x, y) - c_1|^2 \, dx \, dy = \int_{\Omega} |u_0(x, y) - c_1|^2 H(\phi(x, y)) \, dx \, dy$$

$$\int_{\phi<0} |u_0(x, y) - c_2|^2 \, dx \, dy = \int_{\Omega} |u_0(x, y) - c_2|^2 (1 - H(\phi(x, y))) \, dx \, dy \quad (5.27)$$

Therefore the energy function $E(C, c_1, \phi)$ can be written as shown in equation (5.28)

$$E(C, c_1, c_2) = \mu \int_{\Omega} \partial(\phi(x, y)) |\nabla \phi(x, y)| \, dx \, dy + \nu \int_{\Omega} H(\phi(x, y)) \, dx \, dy$$

$$+ \lambda_1 \int_{\Omega} |u_0(x, y) - c_1|^2 H(\phi(x, y)) \, dx \, dy$$

$$+ \lambda_2 \int_{\Omega} |u_0(x, y) - c_2|^2 (1 - H(\phi(x, y))) \, dx \, dy \quad (5.28)$$
The constants $c_1$, $c_2$ are the averages of $u_0$ in $\phi \geq 0$ and $\phi < 0$ respectively. So they are easily computed as shown in equation (5.29)

$$c_1(\phi) = \frac{\int_{\Omega} u_0(x, y)H(\phi(x, y))dxdy}{\int_{\Omega} H(\phi(x, y))dxdy}$$  \hspace{1cm} (5.29)$$

and

$$c_2(\phi) = \frac{\int_{\Omega} u_0(x, y)(1-H(\phi(x, y)))dxdy}{\int_{\Omega} (1-H(\phi(x, y)))dxdy}$$  \hspace{1cm} (5.30)$$

Now the Euler-Lagrange partial differential equation can be deduced. The descent direction $t \geq 0$ can be parameterized, so the equation $\phi (x, y, t)$ is given by equation (5.31)

$$\frac{\partial \phi}{\partial t} = \partial \phi \left[ \mu \text{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right) - \nu - \lambda_1 (u_0 - c_1)^2 + \lambda_2 (u_0 - c_2)^2 \right] = 0$$  \hspace{1cm} (5.31)$$

In order to solve this partial differential equation, $H(z)$ and $\delta(z)$ should be regularized as shown in equation (5.32)

$$H_\varepsilon(z) = \frac{1}{2} + \frac{1}{\pi} \arctan \left( \frac{z}{\varepsilon} \right)$$  \hspace{1cm} (5.32)$$

implying that $\delta(z)$ regularizes as shown in equation (5.33)

$$\delta \varepsilon(z) = \frac{1}{\pi} \cdot \frac{\varepsilon}{\varepsilon^2 + z^2}$$  \hspace{1cm} (5.33)$$
It is easy to see that as \( \varepsilon \to 0 \), \( H_\varepsilon(z) \) converges to \( H(z) \) and \( \partial_\varepsilon(z) \) converges to \( \partial(z) \). It is mentioned that with these regularizations, the algorithm has the tendency to compute a universal minimal.

After discretization and linearization, it becomes as shown in equation (5.34)

\[
\frac{\phi_{i,j}^{n+1} - \phi_{i,j}^n}{\Delta t} = \partial_\varepsilon (\phi_{i,j}^n) \left[ \frac{\mu}{h^2} \Delta^x - \frac{\Delta^y_+ \phi_{i,j}^{n+1}}{\left( \frac{\Delta^x_+ \phi_{i,j}^n}{h^2} + \frac{\Delta^y_+ \phi_{i,j+1}^n - \Delta^y_+ \phi_{i,j-1}^n}{2h^2} \right)} + \frac{\mu}{h^2} \Delta^y - \frac{\Delta^x_+ \phi_{i,j}^{n+1}}{\left( \frac{\Delta^y_+ \phi_{i,j}^n}{h^2} + \frac{\Delta^x_+ \phi_{i,j+1}^n - \Delta^x_+ \phi_{i,j-1}^n}{2h^2} \right)} \right]
\]

\[-\nu - \lambda_1 (u_{0,i,j} - c_1 (\phi^n))^2 + \lambda_2 (u_{0,i,j} - c_2 (\phi^n))^2 \]

(5.34)

where the forward differences of \( \phi_{i,j}^n \) are calculated. This linear system also depends on the forward differences of \( \phi_{i,j}^{n+1} \), which is unfamiliar. However these can be solved using the Jacobi method. In practice, the number of iterations until convergence is found to be small.

5.6 ACTIVE CONTOUR MODELING WITH WAVELETS

The idea of the scale-space continuation method (Leymarie and Levine, 1993) is to calculate the snake in a coarsely smoothed image; then the result at the coarse scale is used as an initial contour on a finer image and so on, until the native image
resolution is reached. The original image is filtered through a family of Gaussian filters with different resolutions. Then, a differentiating filter, such as the Sobel filter, is applied to these Gaussian filtered images to produce approximations of the gradients of the Gaussian smoothed image. The next advance was to implement the gradient-based scale space continuation method by means of a wavelet transform (Liu and Hwang, 1992). In this association it has been shown (Mallat and Zhong, 1992) that the first derivatives of a family of Gaussian filters are equivalent to the corresponding wavelet transform coefficients multiplied by a scaling constant. It has been shown (Mallat, 1998) that fast implementation can be achieved when s is an integer power of 2 by filtering alternatively through a low-pass filter (L) and a highpass filter (H). Then, the external energy at scale s is defined as the negative of the modulus of wavelet transform at scale as shown in equation (5.35)

\[ E_{\text{wavelet}}(x,y) = E_{\text{cts}}(x,y) = -\sqrt{W_1^2I(x,y)^2 + W_2^2I(x,y)^2} \] (5.35)

The above definition of external energy mutually with the continuation method in the wavelet domain represents a generalized version of the gradient-based scale-space continuation method.

This wavelet-based snake model is employed in many experiments on mammogram images. The flow chart of utilized model is shown in Figure.5.2.

Figure 5.3 Flow chart of the wavelet-based active contour model
5.7 SEGMENTATION ALGORITHM

Energy Minimization Algorithm with Jacobi Method is given as:

Initialize $\phi^n$ by $\phi_0$, $n = 0$

for fixed number of iterations do

Compute $c_1(\phi^n)$ and $c_2(\phi^n)$

Estimate forward differences of $\phi^{n+1}$ using Jacobi method

Compute $\phi^{n+1}$

End

Using the energy minimization approach, the desired segmentation is achieved in digital mammogram images.

5.8 EXPERIMENTAL RESULTS

Images from the MIAS (Mammographic Image Analysis Society) database with lesions have been tested. Fig. 5.3(a) shows a sample mammogram image, Figure. 5.3(b-d) shows the detected clusters using FCM clustering, Otsu thresholding and Active contour models respectively.

![Figure. 5.4](image-url)

(a) A sample mammogram image  (b) the detected clusters using FCM clustering, (c) Otsu thresholding and (d) Active contour models
Figure 5.5. Images from the MIAS (Mammographic Image Analysis Society) database with lesions has been tested

Figure 5.3(d) and (5.4) shows the result where the clusters are detected with clear boundaries using active contour model with wavelets than the existing techniques.

Table 5.1 The segmentation error of FCM Clustering, OTSU thresholding and Active Contour Models

<table>
<thead>
<tr>
<th>Number of pixels in the image</th>
<th>Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Figure (b)</td>
</tr>
<tr>
<td>4096</td>
<td>7.81</td>
</tr>
</tbody>
</table>

Table 5.1 shows that the error due to segmentation of the region of interest is less with proposed method whereas it reaches its maximum value of 11.91 for Otsu thresholding method.
5.9 SUMMARY

State-of-the-art image denoising algorithms attempted here, are to recover mammogram lesion detection from their microcalcifications and massive lesions observations, such that the results of the denoising better enhances the mammogram images over the other methods presented. One aspect generally missing in these approaches is that the properties of the residual image (defined as the difference between the noisy observation and the denoised image) have not been well exploited. Here demonstrate the usefulness of residual images in image denoising is demonstrated.

In particular, that well-known full-reference image noise was measured using tools such as fuzzy c-means, OTSU Thresholding and the active contours and the structural similarity was shown and presented. Here different methods to enhance the image quality using different methods were applied and verified by using radiologist observations.