CHAPTER 4

FOLLICLE DETECTION BY OTSU AND HYBRID REGION BASED ACTIVE CONTOUR METHODS

4.1 INTRODUCTION

A fine segmentation algorithm is required for Computer Assisted System (CAS) to detect the follicles automatically in the ovarian images. Image thresholding is a very important problem in automated image analysis. Many image processing and computer vision applications usually require binary images as an introductory step in order to do further processing. By choosing a particular intensity value as “threshold”, images can be segmented by setting those pixels whose original intensity is above the threshold as “white pixels”, and setting the other pixels as “black pixels” and vice versa. Thresholding methods are categorized as listed below.

a. Histogram-shaped-based
b. Clustering-based
c. Entropy-based
d. Attribute similarity methods
e. Object attribute-based
f. Spatial approaches
g. Local methods
Huang, Prewitt, Ridler-Calvard, Li, Kapur, Mean, Kittler-Illingworth, Minimum, Tsai, Otsu, Doyle, Renyi, Shanbhag, Triangle, and Yen are the global thresholding methods, and Bernsen, Mean, Median, MidGrey, Niblack, and Sauvola are the local thresholding methods. Among this, Otsu method is one the most referenced thresholding methods in the literature.

Active contour model is classified into two types, namely, boundary based and region based. The fundamental thought inside active contour model is to develop a curvature, focused to a constraint from input image, in order to detect objects in that image. The method is very robust to initialization. This technique distorts a primary curve so that it separates foreground from background based on the means of the two regions.

This chapter emphasizes on segmentation methods for detection of follicles from ultrasound ovarian images using Otsu, modified Otsu and hybrid region based active contour method and their performance analysis.

4.2 FOLLICLE DETECTION BY OTSU METHOD

In the year 1979, Otsu introduced a method to find the threshold value from the histogram of an image for segmentation. It is a well-performed threshold selection process and has been extensively used for its effectiveness. Otsu's thresholding method entails through all the probable threshold values and computes a measure of pixel levels at each side of the threshold, that is, the pixels which either fall in the foreground or background.

Let the pixels of a given ovarian image be represented in ‘$L$’ gray levels [1, 2, ..., $L$]. The number of pixels at level ‘$j$’ is denoted by $n_j$ and the total number of pixels by $N = n_1 + n_2 + ... + n_L$. $P_j$ is the probability of occurrence of ‘$j$’. In order to simplify the discussion, the gray level histogram
is normalized and considered as a probability distribution which is given by the Equation (4.1)

\[ P_j = \frac{n_j}{N} \]  

(4.1)

where \( P_j \geq 0 \) and \( \sum_{j=1}^{L} P_j = 1 \)

With this normalization, the global mean level \( \mu_T \) of the ovarian image is calculated using Equation (4.2)

\[ \mu_T = \mu(L) = \sum_{j=1}^{L} jP_j \]  

(4.2)

The pixels of the image is then dichotomized into two classes \( g_1 \) and \( g_2 \) (background and objects, or vice versa) by a threshold at level ‘\( t \)’ based on the principle of maximization of between-class variance. \( g_1 \) denotes pixels with levels \([1, \ldots, t]\), and \( g_2 \) denotes pixels with levels \([t + 1, \ldots, L]\). The probability of occurrence of gray level ‘\( j \)’ of the two classes \( g_1 \) and \( g_2 \) are computed using Equation (4.3) and Equation (4.4).

\[ \omega_1 = P_r(g_1) = \sum_{j=1}^{t} P_j = \omega(t) \]  

(4.3)

\[ \omega_2 = P_r(g_2) = \sum_{j=t+1}^{L} P_j = 1 - \omega(t) \]  

(4.4)

Now, the mean levels \( \mu_1 \) and \( \mu_2 \) of the two classes are computed using Equation (4.5) and Equation (4.6)

\[ \mu_1 = \sum_{j=1}^{t} \frac{jP_j}{\omega_1} \]  

(4.5)
\[
\mu_z = \frac{L}{\sum_{j=t+1}^{L} j P_j} \quad (4.6)
\]

where ‘L’ represents the number of gray levels, ‘t’ the threshold and ‘j’ the current iteration. For any choice of gray levels, ‘t’, the mean of the whole image \( \mu_T \) is given by the Equation (4.7)

\[
\omega_1 \mu_1 + \omega_2 \mu_2 = \mu_T 
\quad (4.7)
\]

According to the definition of the variance for a discrete random variable (Otsu 1979) and using the notation \( P_r(j|g_1) \) and \( P_r(j|g_2) \) for the probability of gray level ‘j’, given that the pixel is classified as \( g_1 \) and \( g_2 \) respectively, the class variances are given by the Equation (4.8) and Equation (4.9)

\[
\sigma_1^2 = \sum_{j=1}^{t} (j-\mu_1)^2 P_r(j|g_1) = \sum_{j=1}^{t} (j-\mu_1)^2 \frac{P_j}{\omega_1} \quad (4.8)
\]

\[
\sigma_2^2 = \sum_{j=t+1}^{L} (j-\mu_2)^2 P_r(j|g_2) = \sum_{j=t+1}^{L} (j-\mu_2)^2 \frac{P_j}{\omega_2} \quad (4.9)
\]

where the gray level range varies from 1 to \( L \).

Otsu evaluated the “goodness” of the threshold using the within-class variance \( \sigma_w^2 \) given by Equation (4.10)

\[
\sigma_w^2 = \omega_1 \sigma_1^2 + \omega_2 \sigma_2^2 
\quad (4.10)
\]

and the between-class variance \( \sigma_b^2 \) given by Equation (4.11)

\[
\sigma_b^2 = \omega_1 (\mu_1 - \mu_T)^2 + \omega_2 (\mu_2 - \mu_T)^2 
\quad (4.11)
\]
The total variance $\sigma_T^2$ is described by the Equation (4.12) and Equation (4.13)

$$\sigma_T^2 = \sum_{j=1}^{L} (j - \mu_T)^2 P_j$$  \hspace{1cm} (4.12)$$

$$\sigma_w^2 + \sigma_B^2 = \sigma_T^2$$  \hspace{1cm} (4.13)

The Equation (4.10) requires the computation of within-class variance for each class and for each possible thresholding value, resulting in a very expensive computation that must be avoided (Otsu 1979). The key observation to reduce computation cost is that the calculation of between-class variance is a less expensive step and it can be defined as the within-class variance subtracted from the total variance. Otsu defined the measure of class separability ‘$\eta$’ as in Equation (4.14) that maximize (Otsu 1979) the between-class variance $\sigma_B^2(t)$ by the optimal threshold ‘$t$’

$$\eta = \frac{\sigma_B^2(t)}{\sigma_T^2}$$  \hspace{1cm} (4.14)

Finally, the optimal threshold $t^*$ that maximizes the between-class variance is given by the Equation (4.15)

$$t^* = \max_{1 \leq t < L} (\sigma_B^2(t))$$  \hspace{1cm} (4.15)$$

and that minimizes the within-class variance is given by the Equation (4.16)

$$t^* = \min_{1 \leq t < L} (\sigma_w^2(t))$$  \hspace{1cm} (4.16)

The optimal threshold for segmentation of follicles in ovarian images is obtained by maximizing the between-class variance described by the Equation (4.15). The ovarian images are segmented using this optimal threshold and the implications are shown in Figure 4.1 (a)-(f).
Figure 4.1 Follicle detection by Otsu method a) Input ultrasound ovarian image with follicles b) Result given by the Otsu’s method c) Area open image d) Identified follicles e) Edge detected image f) Overlaid on original image

Figure 4.1(a) shows the input ultrasound ovarian image and Figure 4.1 (b) shows the segmented result of the Otsu method. Area open operation is applied on the segmented image obtained by the Otsu method and the result is shown in Figure 4.1(c). From this result, the number of segmented follicles is identified as two and is represented in two different colours in Figure 4.1(d). This is because of the connected edges of the follicles and is shown in Figure 4.1(e).

In Figure 4.1(f), the segmented results are overlaid on original image. Actually the original ovarian image has more than two follicles and hence it is concluded that the Otsu’s method does not produce satisfactory result as it segments the foreground region along with the background.
4.3 FOLLICLE DETECTION BY MODIFIED OTSU METHOD

In order to improve the segmentation results of the ovarian images for identification of true follicles, the conventional Otsu method is modified. This modified Otsu method iteratively selects the initial threshold value for the Otsu method. In this iterative procedure, the threshold value is initially set as \( T[i] \) which is obtained by the histogram of the image. In the first iteration, for \( i = 1 \), \( T[i] = T[1] \) is determined by computing the average intensity value of the ovarian image. Then, the mean of the intensity values above and below the current threshold value \( T[1] \) are determined and are represented as \( m_1^{[1]} \) and \( m_2^{[1]} \) respectively. The new threshold value \( T[2] \) for the next iteration is computed by taking the average of these two mean values and is given by Equation (4.17).

\[
T[2] = \frac{m_1^{[1]} + m_2^{[1]}}{2}
\]  

(4.17)

The threshold value for the next iteration is generalized in Equation (4.18)

\[
T[i+1] = \frac{m_1^{[i]} + m_2^{[i]}}{2}
\]  

(4.18)

where ‘\( i \)’ is the number of iteration, \( m_1^{[i]} \) and \( m_2^{[i]} \) is the mean of the intensity values above and below the current threshold value \( T[i] \) respectively. The newly calculated threshold value \( T[i+1] \) is carried forward as the threshold value to the next iteration. The iteration proceeds until the difference of the threshold values obtained by two consecutive iterations \( \{T[i+1] - T[i]\} \) converges to zero. This new threshold value \( T[i+1] \) corresponding to the \( [i+1]^{th} \) iteration is now set as the initial threshold value ‘\( t \)’ for the Otsu method.
Thereafter, conventional Otsu thresholding technique is implemented to determine the optimal threshold value ‘$t^*$’ by maximizing the between-class variance.

The various steps in the modified Otsu method is described as follows

(i) $I =$ Input Ovarian Image.

(ii) Set iteration number as $i = 1$.

(iii) The average intensity value of the ovarian image $I$ is computed from its histogram and set as initial threshold $T[i]$.

(iv) With this initial threshold $T[i]$, separate ovarian image $I$ into two groups of pixels, $g_1$ and $g_2$.

(v) Obtain the mean $m_{1[i]}$ and $m_{2[i]}$ of the pixel values in two groups $g_1$ and $g_2$.

(vi) Compute the new threshold value $T[i+1]$ by taking the average of means $m_{1[i]}$ and $m_{2[i]}$ as described in Equation (4.17).

(vii) Find the difference of $T[i+1]-T[i]$.

(viii) If the difference is non zero, repeat from step (iv). If the difference is zero, set this threshold value as the initial threshold ‘$t$’ for the conventional Otsu method. Now, perform the conventional Otsu method.
The proposed modified Otsu method is experimented on ultrasound ovarian images. Table 4.1 lists the threshold values obtained by the Otsu and modified Otsu methods. It is observed that there is a difference between the two threshold values and this difference brings a significant improvement in segmented results.

**Table 4.1** Computed Threshold value by Otsu and modified Otsu methods

<table>
<thead>
<tr>
<th>Ovarian Image</th>
<th>Otsu threshold</th>
<th>Modified Otsu threshold</th>
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<tbody>
<tr>
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<td>19</td>
</tr>
</tbody>
</table>

Figure 4.2(a) shows the original image and Figure 4.2(b), the segmented results of the modified Otsu method.

![Figure 4.2](image_url)

**Figure 4.2** Follicle detection by modified Otsu
a) Original image  
  b) Segmented result by modified Otsu method

From Figure 4.1(b) and Figure 4.2(b), it can be noticed that compared to the conventional Otsu method, the modified Otsu method has
given a better threshold value for separation of the foreground and background regions in ovarian images for segmentation of follicles. Also, it can be noticed from Figure 4.2(b) that the boundary of the follicles is not defined clearly and hence necessitates for an improvement. As the literature survey reported that region based active contour methods can segment edges even more precisely when more suitable initial mask is given and for this reason it is decided to hybridize the modified Otsu with region based active contour technique.

4.4 FOLLICLE DETECTION BY HYBRID REGION BASED ACTIVE CONTOUR METHOD

Region based active contour method can satisfactorily segment images with weak edges and without edges. However, this method fails to automatically find the initial point instead the initial mask has been chosen manually. Moreover, the segmentation result is dependent on the initial mask placement. Poor initialization can produce the contour away from the follicle region. Specifying initial position that is closest to the desired object boundaries improves the segmentation process. Hence, in the process of segmentation of follicles from ovarian images, the problem of automatic placement of the initial mask nearer to the follicle for contour evolution is handled by using the segmented result of the modified Otsu method.

The proposed hybrid region based active contour method for detecting the follicles in ovarian images is based on Chan-Vese model, which can be reformulated in the level set formulation, leading to an easier way to solve the problem. Chan-Vese model for active contours is a powerful and flexible method which is able to segment many types of images, including some that would be quite difficult to segment in means of classical segmentation, using thresholding or gradient based methods (Chan & Vese 2001).
The flow diagram of the hybrid region based active contour method using this level set formulation is shown in Figure 4.3.

Figure 4.3 Flow chart of the hybrid region based active contour method

**Initial mask:** The initial mask for the hybrid region based active contour method is generated using the modified Otsu method. The sample initial mask for the level set algorithm is shown in Figure 4.2(b). This initial mask defines the initial position to evolve the contour.
Compute Signed Distance Function (SDF): Defining the closed contour can be formulated as the level set problem. The level set formulation is represented by the Equation (4.19)

\[
C = \{(x, y), \phi(x, y) = 0\}
\]
\[
\text{inside}(C) = \{(x, y), \phi(x, y) > 0\}
\]
\[
\text{outside}(C) = \{(x, y), \phi(x, y) < 0\}
\] (4.19)

where \(C\) is defined as the intersection between a plane at the 0 level of \(\phi\). This zero level set is being transformed into the desired surface (Aydi et al. 2012). \(\phi(x,y)\) is defined as the Signed Distance Function (SDF) and is shown in Figure 4.4. The contour \(C\) divides \(\phi\) into two open subsets, where \(\phi \geq 0\) inside and \(\phi < 0\) outside.

**Figure 4.4** Signed Distance Function

SDF is used to represent the level set function because they provide the stability and accuracy to the level set method. Hence, SDF is computed from the initial mask generated by the modified Otsu method using Euclidean distance. The first disadvantage of the level set method is the convergence time as it requires more time to make a \(\phi\) change. For faster convergence of the level-set process, narrow-band method has been proposed.
Define curves narrow band: The main idea of narrow band approach is to carry out the level set process in a small region around the level set. The narrow band approach is used to reduce the computation time taken by restricting the updates to a band of grid points that lies near the level set to make a $\phi$ change (Aydi et al. 2012). Values of the $\phi$ are updated to exist within the narrow band. Narrow band curves is given by the Equation (4.20)

$$C_{nb} = \{(i, j), -\beta_0 \leq \phi \leq \beta_0, i = [0, n-1], j = [0, m-1]\}$$  
(4.20)

where $(i,j)$ is defined as pixel coordinates and $(n,m)$ the height and the width of $\phi$. To evolve the contour of the follicles, the force $F$ from the ovarian image and the force from the curvature of the follicles is need to be computed. To compute the force $F$ from the ovarian image, the mean values of the image inside and outside the curve $C$ are to be determined.

Compute the average value of an image inside and outside $C$: The average value of the image inside and outside the curve $C$ is represented as $\mu_{in}$ and $\mu_{out}$ respectively and is computed using Equation (4.21) and Equation (4.22)

$$\mu_{in} = \frac{\sum I(F_{in})}{P_{in}}$$  
(4.21)

$$\mu_{out} = \frac{\sum I(F_{out})}{P_{out}}$$  
(4.22)

where

$F_{in}$ represents the image inside the curve and is described as

$$F_{in} = \{(i, j), \phi > 0, i = [0, n-1], j = [0, m-1]\}$$

$F_{out}$ represents the image outside the curve and is described as

$$F_{out} = \{(i, j), \phi \leq 0, i = [0, n-1], j = [0, m-1]\}$$
$P_{in}$ represents number of elements of $F_{in}$ and $P_{out}$ represents the number of elements of $F_{out}$.

**Computing force from an image:** Chan-Vese energy term $E$ is used to calculate the force $F$ from the ovarian image $I$ and is given in Equation (4.23) and Equation (4.24) (Chan & Vese 2001).

\[ E = \int_{insideC} (I - \mu_{in})^2 + \int_{outsideC} (I - \mu_{out})^2 \]  

(4.23)

or

\[ F = \nabla E \]

\[ F = (I - \mu_{in})^2 + (I - \mu_{out})^2 \]  

(4.24)

**Computing force from a curvature:** The curvature can be calculated using the spatial derivatives of $\phi$ up to second order (Aydi et al. 2012) given by the kappa Equation (4.25)

\[ curvature = \left( \frac{\phi_x^2 \phi_{yy} + \phi_y^2 \phi_{xx} - 2 \phi_x \phi_y \phi_{xy}}{\left( \phi_x^2 + \phi_y^2 \right)^{\frac{3}{2}}} \right) \]  

(4.25)

where $\phi_x^2 = \left( \frac{\partial \phi}{\partial x} \right)^2$ and $\phi_{xx} = \left( \frac{\partial^2 \phi}{\partial x^2} \right)$ denote the first and second-order partial derivatives of $\phi$ with respect to $x$, $\phi_y^2 = \left( \frac{\partial \phi}{\partial y} \right)^2$ and $\phi_{yy} = \left( \frac{\partial^2 \phi}{\partial y^2} \right)$ denote the same with respect to $y$ and $\phi_{xy} = \left( \frac{\partial^2 \phi}{\partial xy} \right)$ denote the second order partial derivative of $\phi$ with respect to $x$ and $y$.

In order to approximate each of the derivatives of $\phi$ according to $x$ and $y$ the Central difference approximation is used and is given by the Equation (4.26).
\[ \phi_x = -\phi\left(P_{\text{left}}\right) + \phi\left(P_{\text{right}}\right) \]
\[ \phi_y = -\phi\left(P_{\text{down}}\right) + \phi\left(P_{\text{up}}\right) \]
\[ \phi_{xx} = -\phi(P_{\text{left}}) - 2\phi(P) + \phi(P_{\text{right}}) \]
\[ \phi_{yy} = -\phi(P_{\text{down}}) - 2\phi(P) + \phi(P_{\text{up}}) \]
\[ \phi_{xy} = -0.25\phi(P_{\text{downleft}}) - 0.25\phi(P_{\text{upright}}) + 0.25\phi(P_{\text{downright}}) + 0.25\phi(P_{\text{upleft}}) \]

(4.26)

The point P(x,y) and their eight neighbor points named \{P_{\text{up}}, P_{\text{down}}, P_{\text{left}}, P_{\text{right}}, P_{\text{upright}}, P_{\text{upleft}}, P_{\text{downright}}, P_{\text{downleft}}\} are defined in Figure 4.5.

**Figure 4.5** Central difference approximation scheme

**Evolvement of the curve:** Each of the derivatives of \( \phi \) is estimated in relation to \( x \) and \( y \). In Equation (4.27), the value of \( \phi \) after a small time interval \( \Delta t \) is approximated by the first-order Taylor expansion given by Equation (4.27)

\[ \phi((x, y), t + \Delta t) = \Delta t \phi_t + \phi((x, y), t) \]  
(4.27)
where, the gradient descent \( \phi_t = \alpha \cdot \text{curvature} + \frac{F}{\max |F|} \) and the time step
\[
\Delta t = \frac{1}{(\max(\phi_t) + \epsilon)} .
\]

The parameter ‘\( \alpha \)’ is the weight of a smoothing term and ‘\( \epsilon \)’ is coefficient to satisfy Courant-Friedrichs-Lewy (CFL) condition. Since the movement of the zero level set during the level-set iteration is bounded in each step by the CFL condition, it is possible to restrict the level-set process to a band around the zero level set without losing flexibility or distorting the result (Phillips, C 1999). If this condition is not respected, it will produce an incorrect contour. CFL condition is also an essential (Aydi et al. 2012) condition for convergence while solving certain partial differential equations.

**Maintaining a smooth condition of \( \phi \):** The Sussman function is used to smooth the Signed Distance Function (SDF) and is given in Equation (4.28)

\[
\phi_{i,j}^{M+1} = \phi_{i,j}^M - \Delta t S_\epsilon(\phi_{i,j}) G(\phi_{i,j}^M)
\]

(4.28)

where \( S \) is a sign function and smoothing of the sign function is done using the expression
\[
S_\epsilon(\phi_{i,j}) = \frac{\phi_{i,j}^2}{\sqrt{\phi_{i,j}^2 + \epsilon^2}}
\]

and \( G \) is the gradient function described by the expressions

\[
G(\phi_{i,j}^+) = \sqrt{(\max((A^+)^2,(B^+)^2) + \max((C^+)^2,(D^+)^2))} - 1, \quad \text{if } \phi > 0
\]

\[
G(\phi_{i,j}^-) = \sqrt{(\max((A^-)^2,(B^-)^2) + \max((C^-)^2,(D^-)^2))} - 1, \quad \text{if } \phi < 0
\]

\[
G(\phi_{i,j}^0) = 0, \quad \text{otherwise}
\]

\( A^+ (A^-) \) is a matrix that has the positive as well as the negative values of \( A \) and zero otherwise. The other matrix (\( B, C \) and \( D \)) are manipulated in the same way.
\[
A = \phi_{i,j} - \phi_{i-1,j} = \{a_{i,j}, i = 0..n-1 \text{ and } j = 0..m-1\}
\]
\[
B = \phi_{i+1,j} - \phi_{i,j} = \{b_{i,j}, i = 0..n-1 \text{ and } j = 0..m-1\}
\]
\[
C = \phi_{i,j} - \phi_{i,j-1} = \{c_{i,j}, i = 0..n-1 \text{ and } j = 0..m-1\}
\]
\[
D = \phi_{i,j+1} - \phi_{i,j} = \{d_{i,j}, i = 0..n-1 \text{ and } j = 0..m-1\}
\]

This hybrid region based active contour method is applied on ultrasound ovarian image to segment the follicles in the ovary. The result of the hybrid region based active contour method is represented in Figure 4.6.

![Figure 4.6 Follicle detection by hybrid region based active contour method](image)

a) Input ovary image  b) Histogram  c) Initial mask produced by modified Otsu  d) Detected follicles  e) Follicle count  f) Edge detected image  g) The result overlaid on original image  h) Follicles marked by medical expert
Figure 4.6(a) shows the input ovarian image, Figure 4.6(b) the histogram plot of the image, Figure 4.6(c) the initial mask generated by the modified Otsu method, the detected follicles and the count are given in Figure 4.6(d) and Figure 4.6(e) respectively. Figure 4.6(f) shows the edges of the follicles and Figure 4.6(g) displays the follicles overlaid on the original image. The follicles marked by the medical expert are shown in Figure 4.6(h).

In this process, the input mask image is resized and number of iteration $m_{\text{iteration}}$ is set as 50. Normally, the conventional contour method detects the follicle region at its 400th iteration. But, the hybrid region based active contour method identified the follicular region and the edges of follicles in the 50th iteration itself for all the test images used in this study. This is mainly because of the choice of the initial mask that is nearer to the object, which is the segmented result of the modified Otsu method. Thereby, the proposed hybrid region based active contour method based on Otsu has detected the follicles in less number of iterations and hence with less computational time. The process has also detected the follicles without user interaction and hence the segmentation is automated.

In this method, the parameter used to limit the narrow band border is chosen as $[-1.2, 1.2]$, $\alpha=0.9$ and $\varepsilon=0.45$ are passed as inputs for the hybrid region based active contour. These parameters are selected empirically based on the best results of segmentation of ovarian images for follicle detection.
Table 4.2 shows the segmentation results of hybrid region based active contour method for twelve ovarian images taken for discussion.

Table 4.2  Ovarian follicle detection by Hybrid region based active contour method and Medical expert

<table>
<thead>
<tr>
<th>Database Image</th>
<th>Original Image</th>
<th>Segmented Follicles</th>
<th>Superimposed on Original Image</th>
<th>Medical Expert Result</th>
</tr>
</thead>
<tbody>
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<td>oi001</td>
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<td><img src="image2.png" alt="Segmented Follicles" /></td>
<td><img src="image3.png" alt="Superimposed" /></td>
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<td><img src="image16.png" alt="Medical Expert Result" /></td>
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<tr>
<td>Database Image</td>
<td>Original Image</td>
<td>Segmented Follicles</td>
<td>Superimposed on Original Image</td>
<td>Medical Expert Result</td>
</tr>
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<td>oi024</td>
<td><img src="image1" alt="Original Image" /></td>
<td><img src="image2" alt="Segmented Follicles" /></td>
<td><img src="image3" alt="Superimposed" /></td>
<td><img src="image4" alt="Medical Expert Result" /></td>
</tr>
<tr>
<td>oi032</td>
<td><img src="image5" alt="Original Image" /></td>
<td><img src="image6" alt="Segmented Follicles" /></td>
<td><img src="image7" alt="Superimposed" /></td>
<td><img src="image8" alt="Medical Expert Result" /></td>
</tr>
<tr>
<td>oi049</td>
<td><img src="image9" alt="Original Image" /></td>
<td><img src="image10" alt="Segmented Follicles" /></td>
<td><img src="image11" alt="Superimposed" /></td>
<td><img src="image12" alt="Medical Expert Result" /></td>
</tr>
<tr>
<td>oi056</td>
<td><img src="image13" alt="Original Image" /></td>
<td><img src="image14" alt="Segmented Follicles" /></td>
<td><img src="image15" alt="Superimposed" /></td>
<td><img src="image16" alt="Medical Expert Result" /></td>
</tr>
<tr>
<td>oi063</td>
<td><img src="image17" alt="Original Image" /></td>
<td><img src="image18" alt="Segmented Follicles" /></td>
<td><img src="image19" alt="Superimposed" /></td>
<td><img src="image20" alt="Medical Expert Result" /></td>
</tr>
</tbody>
</table>
The results of the Otsu, Modified Otsu, Active Contour and Hybrid Region based Active Contour methods are compared with the ground truth to evaluate their performances. Three quality indices, namely, Probabilistic Rand Index (PRI), Global Consistency Error (GCE) and Variation of Information (VOI) are selected to evaluate the performance of the methods and quality of their results. (Kumar & Arthanariee 2014; Sardana 2013; Xess & Agnes 2014). The values of PRI should be higher and on the other hand the values of GCE and VOI should be low.

<table>
<thead>
<tr>
<th>Database Image</th>
<th>Original Image</th>
<th>Segmented Follicles</th>
<th>Superimposed on Original Image</th>
<th>Medical Expert Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>oi099</td>
<td><img src="image1" alt="Image" /></td>
<td><img src="image2" alt="Image" /></td>
<td><img src="image3" alt="Image" /></td>
<td><img src="image4" alt="Image" /></td>
</tr>
<tr>
<td>oi110</td>
<td><img src="image5" alt="Image" /></td>
<td><img src="image6" alt="Image" /></td>
<td><img src="image7" alt="Image" /></td>
<td><img src="image8" alt="Image" /></td>
</tr>
<tr>
<td>oi135</td>
<td><img src="image9" alt="Image" /></td>
<td><img src="image10" alt="Image" /></td>
<td><img src="image11" alt="Image" /></td>
<td><img src="image12" alt="Image" /></td>
</tr>
</tbody>
</table>

### 4.5 PERFORMANCE ANALYSIS

The results of the Otsu, Modified Otsu, Active Contour and Hybrid Region based Active Contour methods are compared with the ground truth to evaluate their performances. Three quality indices, namely, Probabilistic Rand Index (PRI), Global Consistency Error (GCE) and Variation of Information (VOI) are selected to evaluate the performance of the methods and quality of their results. (Kumar & Arthanariee 2014; Sardana 2013; Xess & Agnes 2014). The values of PRI should be higher and on the other hand the values of GCE and VOI should be low.
4.5.1  Probabilistic Rand Index (PRI)

Rand index is the function that converts the problem of comparing two partitions with possibly differing number of classes into a problem of computing pair wise label relationships. The PRI computes the fraction of pairs of pixels whose labelling are consistent between the calculated segmentation and the ground truth. It is a measure of resemblance between two data groups. The PRI gives values between zero to one. If two segmented results have no similarities, the result is zero and if the segmented images are identical, the result is one. The formula for PRI is defined in Equation (4.29)

\[
PR(R_{test}, \{R_{GT}\}) = \frac{1}{\binom{n}{2}} \sum_{i<j} [c_{ij} p_{ij} + (1-c_{ij})(1-p_{ij})]
\]  

(4.29)

where \(R_{GT}\) are the manually segmented ground truth images \(\{R_1, R_2, \ldots, R_{GT}\}\) corresponding to the segmented ovarian images \(Y = \{Y_1, Y_2, \ldots, Y_n\}\) by the algorithm. The set of all perceptually correct segmentations is defined by the random number \(p_{ij}\).

\[
c_{ij} = I(R^R_{test} = L^P_{test})
\]  

(4.30)

In Equation (4.30), \(c_{ij}\) indicate the event of a pair of pixel ‘i’ and ‘j’ having the same label in the test image \(R_{test}\).

4.5.2  Global Consistency Error (GCE)

The GCE is a measure to appraise the extent to which one segmentation result is a refinement of the other. If one segment is an appropriate subset of the other, then the pixel lies within the area of refinement and the error must be zero. If there is no subset relationship, then it signifies
that the two regions overlap in an inconsistent manner (Kumar & Arthanariee 2014; Sardana 2013; Xess & Agnes 2014). The GCE is used as a measure to compare the results of the proposed segmentation method \((I_1)\) to ground truth \((I_2)\).

The GCE is measured by using Equation (4.31).

\[
GCE = \frac{1}{N} \min \{ \sum a p_a(I_1, I_2), \sum a p_a(I_2, I_1) \}  
\]

(4.31)

For a given pixel \(p_a\), in the segmented image \(I_1\) and the ground truth \(I_2\), the GCE measure produces a real valued output in the range \([0:1]\), where zero signifies no error.

4.5.3 Variation of Information (VOI)

The VOI is a measure of the distance between two classes. It measures the sum of information loss and information gain between the two classes, and thus it roughly measures the extent to which one class can explain the other (Kumar & Arthanariee 2014). The VOI metric is nonnegative and a lower value indicates greater similarity.

\[
\text{VoI}(X, X') = E(X) + E(X') - 2I(X, X') 
\]

(4.32)

In Equation (4.32), where \(E(X)\) is entropy of \(X\) and \(I(X,X')\) is mutual information between \(X\) and \(X'\).
The comparative analysis of Otsu, modified Otsu, active contour and hybrid region based active contour methods with the ground truth based on the PRI metric is given in Table 4.3.

<table>
<thead>
<tr>
<th>Image</th>
<th>Otsu</th>
<th>Modified Otsu</th>
<th>Active Contour</th>
<th>Hybrid Region Based Active Contour</th>
</tr>
</thead>
<tbody>
<tr>
<td>oi001</td>
<td>0.4820</td>
<td>0.8645</td>
<td>0.5851</td>
<td>0.8605</td>
</tr>
<tr>
<td>oi002</td>
<td>0.6608</td>
<td>0.9265</td>
<td>0.4975</td>
<td>0.9223</td>
</tr>
<tr>
<td>oi013</td>
<td>0.4442</td>
<td>0.8880</td>
<td>0.5195</td>
<td>0.9414</td>
</tr>
<tr>
<td>oi022</td>
<td>0.6246</td>
<td>0.8987</td>
<td>0.8216</td>
<td>0.9531</td>
</tr>
<tr>
<td>oi024</td>
<td>0.7182</td>
<td>0.8099</td>
<td>0.8255</td>
<td>0.9642</td>
</tr>
<tr>
<td>oi032</td>
<td>0.6032</td>
<td>0.9552</td>
<td>0.6827</td>
<td>0.9739</td>
</tr>
<tr>
<td>oi049</td>
<td>0.6159</td>
<td>0.9715</td>
<td>0.5789</td>
<td>0.9689</td>
</tr>
<tr>
<td>oi056</td>
<td>0.4767</td>
<td>0.6720</td>
<td>0.5457</td>
<td>0.9469</td>
</tr>
<tr>
<td>oi063</td>
<td>0.6247</td>
<td>0.8536</td>
<td>0.5828</td>
<td>0.8951</td>
</tr>
<tr>
<td>oi099</td>
<td>0.4457</td>
<td>0.9503</td>
<td>0.5083</td>
<td>0.9634</td>
</tr>
<tr>
<td>oi110</td>
<td>0.4589</td>
<td>0.9015</td>
<td>0.4935</td>
<td>0.9150</td>
</tr>
<tr>
<td>oi135</td>
<td>0.8442</td>
<td>0.9346</td>
<td>0.5858</td>
<td>0.9385</td>
</tr>
</tbody>
</table>

The results show that the PRI value for hybrid region based active contour method is maximum and nearly equal to 1, thus resembling the result of medical expert. The graphical representation of the PRI metric for the four different methods is given in Figure 4.7.
Figure 4.7 Graphical representation of Probabilistic Rand Index of Otsu, Modified Otsu, Active contour and Hybrid region based active contour methods

Table 4.4 represents the GCE values computed for the Otsu, modified Otsu, active contour and hybrid region based active contour methods.

Table 4.4 Comparative Analysis of Global Consistency Error of Otsu, Modified Otsu, Active contour and Hybrid region based active contour methods

<table>
<thead>
<tr>
<th>Image</th>
<th>Otsu</th>
<th>Modified Otsu</th>
<th>Active Contour</th>
<th>Hybrid Region Based Active Contour</th>
</tr>
</thead>
<tbody>
<tr>
<td>oi001</td>
<td>0.2100</td>
<td>0.0990</td>
<td>0.1930</td>
<td>0.1249</td>
</tr>
<tr>
<td>oi002</td>
<td>0.1037</td>
<td>0.0455</td>
<td>0.1306</td>
<td>0.0520</td>
</tr>
<tr>
<td>oi013</td>
<td>0.1137</td>
<td>0.0622</td>
<td>0.1095</td>
<td>0.0454</td>
</tr>
<tr>
<td>oi022</td>
<td>0.1886</td>
<td>0.0717</td>
<td>0.1168</td>
<td>0.0343</td>
</tr>
<tr>
<td>oi024</td>
<td>0.0650</td>
<td>0.0613</td>
<td>0.0631</td>
<td>0.0255</td>
</tr>
<tr>
<td>oi032</td>
<td>0.1241</td>
<td>0.0363</td>
<td>0.1206</td>
<td>0.0243</td>
</tr>
<tr>
<td>oi049</td>
<td>0.1094</td>
<td>0.0251</td>
<td>0.1204</td>
<td>0.0239</td>
</tr>
<tr>
<td>oi056</td>
<td>0.1367</td>
<td>0.1207</td>
<td>0.1449</td>
<td>0.0515</td>
</tr>
<tr>
<td>oi063</td>
<td>0.1369</td>
<td>0.1009</td>
<td>0.1510</td>
<td>0.0852</td>
</tr>
<tr>
<td>oi099</td>
<td>0.1118</td>
<td>0.0329</td>
<td>0.1071</td>
<td>0.0250</td>
</tr>
<tr>
<td>oi110</td>
<td>0.2207</td>
<td>0.0886</td>
<td>0.2294</td>
<td>0.0756</td>
</tr>
<tr>
<td>oi135</td>
<td>0.1125</td>
<td>0.0746</td>
<td>0.2258</td>
<td>0.0739</td>
</tr>
</tbody>
</table>
The GCE value is expected to be lower value for better segmentation. The hybrid region based active contour method has a lower GCE value. Figure 4.8 gives the graphical representation of the GCE values of the four different methods.

![Graphical representation of Global Consistency Error of Otsu, Modified Otsu, Active contour and Hybrid region based active contour methods](image)

**Figure 4.8** Graphical representation of Global Consistency Error of Otsu, Modified Otsu, Active contour and Hybrid region based active contour methods

The comparative analysis of Otsu, modified Otsu, active contour and the hybrid region based active contour methods based on VOI metric is given in Table 4.5. The graphical representation of VOI metric for four different methods is given in Figure 4.9.
Table 4.5 Comparative Analysis of Variation of Information of Otsu, Modified Otsu, Active contour and Hybrid region based active contour methods

<table>
<thead>
<tr>
<th>Image</th>
<th>Otsu</th>
<th>Modified Otsu</th>
<th>Active Contour</th>
<th>Hybrid Region Based Active Contour</th>
</tr>
</thead>
<tbody>
<tr>
<td>oi001</td>
<td>2.1585</td>
<td>1.0553</td>
<td>1.5214</td>
<td>0.9180</td>
</tr>
<tr>
<td>oi002</td>
<td>1.6158</td>
<td>0.5832</td>
<td>1.4381</td>
<td>0.5577</td>
</tr>
<tr>
<td>oi013</td>
<td>2.1116</td>
<td>0.7867</td>
<td>1.4406</td>
<td>0.4674</td>
</tr>
<tr>
<td>oi022</td>
<td>1.6730</td>
<td>0.6490</td>
<td>0.8907</td>
<td>0.3719</td>
</tr>
<tr>
<td>oi024</td>
<td>1.2804</td>
<td>0.8883</td>
<td>0.8132</td>
<td>0.3046</td>
</tr>
<tr>
<td>oi032</td>
<td>1.7237</td>
<td>0.3833</td>
<td>1.1427</td>
<td>0.2616</td>
</tr>
<tr>
<td>oi049</td>
<td>1.7908</td>
<td>0.2778</td>
<td>1.3881</td>
<td>0.2697</td>
</tr>
<tr>
<td>oi056</td>
<td>2.2258</td>
<td>1.6548</td>
<td>1.5916</td>
<td>0.4987</td>
</tr>
<tr>
<td>oi063</td>
<td>1.7445</td>
<td>1.0623</td>
<td>1.5680</td>
<td>0.7959</td>
</tr>
<tr>
<td>oi099</td>
<td>2.0707</td>
<td>0.3891</td>
<td>1.4939</td>
<td>0.2863</td>
</tr>
<tr>
<td>oi110</td>
<td>2.3847</td>
<td>0.8731</td>
<td>1.7406</td>
<td>0.7582</td>
</tr>
<tr>
<td>oi135</td>
<td>1.2858</td>
<td>0.8105</td>
<td>1.8775</td>
<td>0.7591</td>
</tr>
</tbody>
</table>

Figure 4.9 Graphical representation of Variation of Information of Otsu, Modified Otsu, Active contour and Hybrid region based active contour methods
Table 4.6 gives the number of follicles segmented by the four different methods from the ovarian images taken for discussion.

Table 4.6  Number of detected follicles on ovarian images

<table>
<thead>
<tr>
<th>Image</th>
<th>Otsu</th>
<th>Modified Otsu</th>
<th>Active Contour</th>
<th>Hybrid Region Based Active Contour</th>
<th>Medical Expert</th>
</tr>
</thead>
<tbody>
<tr>
<td>oi001</td>
<td>6</td>
<td>11</td>
<td>1</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>oi002</td>
<td>8</td>
<td>4</td>
<td>1</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>oi013</td>
<td>6</td>
<td>7</td>
<td>1</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>oi022</td>
<td>5</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>oi024</td>
<td>9</td>
<td>5</td>
<td>1</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>oi032</td>
<td>7</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>oi049</td>
<td>10</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>oi056</td>
<td>20</td>
<td>17</td>
<td>1</td>
<td>12</td>
<td>17</td>
</tr>
<tr>
<td>oi063</td>
<td>14</td>
<td>14</td>
<td>3</td>
<td>9</td>
<td>16</td>
</tr>
<tr>
<td>oi099</td>
<td>1</td>
<td>5</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>oi110</td>
<td>2</td>
<td>7</td>
<td>1</td>
<td>7</td>
<td>7</td>
</tr>
<tr>
<td>oi135</td>
<td>15</td>
<td>12</td>
<td>1</td>
<td>11</td>
<td>11</td>
</tr>
</tbody>
</table>

Except for images oi001, oi056 and oi063, the proposed hybrid region based active contour method has segmented the follicles correctly and is found to be same as manual results, which can be easily observed from the Figure 4.10. It is inferred from the results that the hybrid region based active contour method has outperformed, the other Otsu based methods.
4.6 SUMMARY

This chapter has presented Otsu, modified Otsu, region based active contour and hybrid region based active contour methods for detection of follicles in ovarian images. Initially, conventional Otsu method is used to segment the follicles and improvised in modified Otsu method to obtain the better threshold. However, a few background regions are identified as follicles. This necessitated further improvement in segmentation of follicles.

Region based active contour method can overcome the problem of background elimination, but needs manual intervention for identifying the contour of the follicles. For better elimination of the background information and to automate the segmentation process, the segmented output of the modified Otsu method is set as the initial mask in the region based active contour method. This thought has helped to detect the follicles more accurately in less number of iterations, as initial mask is more nearer to the object to be segmented. Hence, the proposed hybrid region based active contour method is found to be computationally efficient.
The performances of the methods are evaluated using PRI, GCE and VOI metrics. The proposed hybrid region based active contour method achieves a higher PRI and lower GCE and VOI values than the existing methods. Hence, the proposed hybrid region based active contour method could predict the follicles more accurately and perform better than the existing methods. However, the results report that the few follicles are not identified correctly and the segmentation process needs further development.