CHAPTER 3

REVIEW OF IMAGE SEGMENTATION METHODS

3.1 Introduction

Image segmentation is one of the most important steps in image partitioning and their analyses. It can be used for various applications in computer vision and digital image processing. Many of the applications require highly accurate and computationally faster image processing algorithms. The success of any application depends on reliability and accuracy of the image processing used. In this chapter, we have studied, reviewed and analyzed important threshold and region based image segmentation techniques and their variations.

3.2 Image Segmentation Techniques

Fundamental steps in digital image processing are shown in Fig 3.1. Image acquisition digitizes the image captured by camera. Image enhancement is the process of manipulating an image so that the results are more suitable for specific applications. Image restoration improves an appearance of an image which tends to probabilities model of image degradation. Morphological processes are the tools of extracting image components that are useful in the description and presentation of an image. Image segmentation is the most difficult ask in digital image processing which separates objects from the background. Representation makes the decision whether to represent data as boundary or as a complete region. Recognition is the process that assigns label to an object based on information provided by its descriptor.
3.2.1 Threshold Based Segmentation

Thresholding is one of the simplest approaches for image segmentation based on intensity levels. Threshold based technique works on the assumption that the pixels falling in certain range of intensity values represents one class and remaining pixels in the image represents the other class. Thresholding can be implemented either locally or globally [84]. For global thresholding brightness
threshold value is to be selected to segment the image into object and background. It generates binary image from given input image. The pixels satisfying threshold test are considered as object pixels with binary value ‘1’ and other pixels are treated as background pixels with binary value ‘0’.

\[
g(u, v) = \begin{cases} 
1, & f(u, v) \geq T \\
0, & \text{Otherwise}
\end{cases}
\]  

(3.1)

where T is predefined threshold.

Selection of threshold is very crucial in image segmentation process. Threshold value can be determined either by an interactive way or can be the outcome of automatic threshold selection method [85]. N. Otsu method is optimal for thresholding large objects from the background [86]. Threshold based approaches are computationally inexpensive fast and can be used for real time applications. A single global threshold partitions image into objects and background, but objects may have different characteristic grey value. In such situations multiple threshold values are needed, for applying over different areas of the image. Threshold value for each region is local threshold and the process is multilevel thresholding [87] which helps to detect different objects in an image separately.

Steps for multilevel thresholding are:

- Divide image into subparts.
- Select local threshold for each subpart of image.
- Compare the pixels for individual subpart and segment the region.
- Repeat the process for each subpart and stop when all subparts are segmented.
Let us consider an image with two different objects, then identify two thresholds $T_1$ and $T_2$ such that

$$\begin{align*}
T_1 &\leq f(u,v) \leq T_2 & \text{for one object} \\
f(u,v) &\geq T_2 & \text{for the other object} \\
f(u,v) &\leq T_1 & \text{for the background}
\end{align*}$$

(3.2)

Fig 3.2 (a) represents thresholding of an image with one light object and shady background, and fig 3.2 (b) two different light objects and dark background.

3.2.2 Region Based Segmentation

In region based segmentation regions are constructed by associating or dissociating neighbor pixels. It works on the principle of homogeneity, by considering the fact that neighboring pixels inside a region possess similar characteristics and dissimilar to the pixels in other regions. Each pixel is compared with its neighboring pixel for similarity check such as grey level, color, texture, shape. If the result is positive then that particular pixel is added to the pixel to grow the region.
If complete image is denoted as region $R$, then for segmentation compose it into $n$ disjoint regions $S_1, S_2, S_3, \ldots, S_n$ such that

\[
\bigcup S_i = S, \quad S_i \cap S_j = \emptyset, \quad \text{if } i \neq j
\]

\[
Prop(S_i) = \begin{cases} 
    \text{True}, & \text{if } i = 1, 2, 3, \ldots, n \\
    \text{False}, & \text{if } i = 1, 2, 3, \ldots, n 
\end{cases}
\]

(3.3)

Where $Prop(S_i)$ is defined in terms of feature values over region $R$. These regions are connected disjoint and homogeneous in nature [88].

Region based method is classified in two categories such as region growing and region split and merge.

### 3.2.2.1 Region Growing Method

In this method pixels in a region are labeled with a unique label which is different from the labels of other regions [89]. This method can further be classified as Seeded Region Growing (SRG) and Unseeded Region Growing (UsRG). SRG is semiautomatic method and UsRG is fully automatic method [90].

- **Seeded Region Growing (SRG)**

  It is proposed by R. Adam [91]. SRG is robust, rapid and is free from tuning parameters. The process starts by selecting a seed pixel within the image. The proper choice of seed is very crucial in this method, since it is concerned with overall segmentation quality.

  General steps in SRG algorithm are:

  - Select seed pixel within image to start segmentation process.
  - Decide criteria to grow the region.
  - Include pixel in the region if it is 8-connected to at least one of the pixel in the region.
  - Label all the regions, after testing all the pixels for allocation.
- Merge regions if two different regions get same label.

**Fig. 3.3: Seeded Region Growing**

- **Unseeded Region Growing (UsRG)**
This method is based on pixel similarities within the region. UsRG is flexible, fully automatic and does rely on tuning parameters. General steps in UsRG algorithm are:
  - Initialize segmentation process with region $S_1$ containing single pixel and eventually results in $S_1, S_2, ..., S_n$ regions after completion.
  - For pixel allocation, difference measure of the test pixel with the mean value of the statistics is considered.
  - Allocate the pixel to the specific region say $S_i$ if difference value is less than certain threshold; otherwise allocate the pixel to new region $S_j$.
  - Repeat above steps for all remaining pixels.
3.2.2.2 Region Split and Merge Method

This method proposed by B. Penetal [92] works on the basis of quadtree with main objective to distinguish the homogeneity of the image. In this method entire image is considered as one single region and then divide the image into four different quadrants based on certain predefined criteria. Fig. 3.4 illustrates the method.

![Fig. 3.4: Region Split and Merge method](image)

General steps in this method are:

- Define homogeneity condition.
- Create pyramid data structure for image.
- Form a quadtree with level numbers and form fragment number at node
- Repeat the process until no more splitting or merging is possible.

3.2.3 Discontinuity Based Segmentation

Segmentation by this method is based on the principle of intensity variations among the pixels. Object boundaries leads to formation of edges. The significant sudden changes in the intensity levels among neighboring pixels in certain direction are termed as edges and results in the discontinuity in the pixels. Smoothing, detection and localization are the steps involved in edge detection [93]. Edges are usually found by applying masks over the image. Edges in the
given image are detected by using gradient or the zero crossing technique. The convolution between mask and the image determines the edge set for image. Edge detection operators are first derivative operator and second derivative operator [94]. Gradient for first derivative operator is

\[
\nabla f = G[f(u, v)] = \begin{bmatrix}
\frac{\partial f}{\partial u} \\
\frac{\partial f}{\partial v}
\end{bmatrix}
\]

(3.4)
direction of gradient is \(\theta = \tan^{-1}\left[ \frac{h_y}{h_x} \right] \) where \(\theta\) is measured with respect to \(X\)-axis. Operators used in this type are Robert’s operator, Prewitts operator, Sobels operator etc. Second order derivative operator works on zero crossing detection, gradient for this operator is

\[
\nabla^2 = \frac{\partial^2 f}{\partial u^2} + \frac{\partial^2 f}{\partial v^2}
\]

(3.5)
where

\[
\frac{\partial^2 f}{\partial u^2} = f(u, v + 1) - 2f(u, v) + f(u, v - 1)
\]

\[
\frac{\partial^2 f}{\partial v^2} = f(u + 1, v) - 2f(u, v) + f(u - 1, v),
\]

operators used in this type are Laplacian of Gaussian and Canny Edge operator.

3.2.4 Clustering Based Segmentation

In cluster based segmentation, data is combined into groups such that the data with similar features will fall in one group whereas the data clusters are being different from each other [95]. The \(k\)-means algorithm is commonly used for determining the organization of the data [96]. This unsupervised clustering approach has a strong affinity to get trapped into local minima while generating an optimal solution and hence it makes clustering wholly dependent on the primary cluster centers distribution. Hence, the proper choice of correct initial parameters is most challenging as well the clustering algorithms needs thorough
study to identify correct input parameters for getting optimal or suboptimal clustering results.

- **k-means algorithm**

In this algorithm number of desired clusters needs to be decided initially. $k$-means algorithm minimizes the total distance between data points and cluster centre. Steps involved in $k$-means algorithm are:

- Decide number of desired clusters $k$, randomly set the $k$-cluster centers at different initial locations in the image.
- Assign each pixel to the cluster having center nearest to that respective pixel.
- Compute new cluster center, which should be average co-ordinates of data points.
- Repeat the process until no more changes are required.

### 3.2.5 Fuzzy C - means Clustering Method (FCM)

Fuzzy $C$ - means method proposed by Y. Yang [97] is an iterative clustering method for color image segmentation. In this method pixel can belong to more than one cluster and set of membership level is associated with each pixel. FCM requires cluster center along with objective function. FCM generates fuzzy partition matrix.

Objective function for FCM is

$$J_{FCM} = \sum_{j=1}^{c} \sum_{i=1}^{p} (u_{ij})^q d^2(p_j, u_i)$$  \hspace{1cm} (3.6)

where $p = \{p_1, p_2, \ldots, p_n\} \in R$

$n$ – Number of data points

c – Number of clusters, $2 \leq c \leq n$
\( u_{ij} \) – Degree of membership of \( p_j \) in \( i^{th} \) cluster

\( u_i \) – Prototype centre of cluster \( i \)

\( q \) – Weighting exponent of fuzzy member

\( d^2(p_j, u_i) \) – Distance between object \( p_j \) and cluster \( u_i \)

FCM algorithm steps are:

- Assign the values for \( c, q, \) threshold \( \varepsilon \) and initialize the partition matrix 
  
  \[ U = [u_{ij}] \]

  cluster center and counter \( l \).

- Store membership value in array

- for each iteration, calculate parameters \( a_i^l, b_i^l \) for all pixels.
  
  \[ a_i^l = a_i^{l-1} + v_i p_k, b_i^l = b_i^{l-1} + v_i \]

- Update cluster centre after each iteration and compare with previous
  
  value \( U^l - U^{l-1} \)

- If difference of comparison is less than the defined threshold then stop
  
  iteration, otherwise repeat the process,
### 3.3 Analysis of Image segmentation methods

Table 3.1 summarizes the advantages and disadvantages of image segmentation methods proposed in the literature.

<table>
<thead>
<tr>
<th>Method</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Threshold based Method</td>
<td>• Does not require prior information of the image.</td>
<td>• For an image with broad and flat valleys or without any peak, it doesn’t work well.</td>
</tr>
<tr>
<td></td>
<td>• Computationally inexpensive.</td>
<td>• Neglects spatial information of an image, cannot guarantee that the segmented regions are contiguous.</td>
</tr>
<tr>
<td></td>
<td>• Fast and simple for implementation.</td>
<td>• Highly noise sensitive.</td>
</tr>
<tr>
<td></td>
<td>• Can be used in real time applications.</td>
<td>• Selection of threshold is crucial, wrong choice may result into over or under segmentation.</td>
</tr>
<tr>
<td>Region based Method</td>
<td>• Gives better result in comparison with other segmentation methods.</td>
<td>• Sequential by nature and quite expensive in both computation time and memory.</td>
</tr>
<tr>
<td></td>
<td>• Provides flexibility to choose between interactive and automatic technique for image segmentation.</td>
<td>• To decide stopping criteria for segmentation is difficult task.</td>
</tr>
<tr>
<td></td>
<td>• Flow from inner point to outer region generates clear object boundaries.</td>
<td>• Scan order dependencies may be yielded in SRG and can have considerable impact on minute regions.</td>
</tr>
<tr>
<td></td>
<td>• Proper selection of seed gives accurate result than any other method.</td>
<td>• Selection of noisy seed by user leads to flawed segmentation.</td>
</tr>
<tr>
<td>Method</td>
<td>Advantages</td>
<td>Disadvantages</td>
</tr>
<tr>
<td>------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
</tbody>
</table>
| Discontinuity based    | • Works well for images having good contrast between regions.  
                           • Second order differential operator gives reliable result.                                                                                                                                            | • For all type of images, single operator doesn’t suits.  
                           • Size of operator and computational complexity are proportional to each other.  
                           • Generally boundaries determined are discontinuous.                                                                                                                                                    |
| Method                 |                                                                                                                                                                                                             |                                                                                                                                                                                                           |
| Cluster based          | • For small values of $k$, $k$-means is computationally faster.  
                           • Eliminates noisy spots.  
                           • Reduces false blobs.  
                           • More homogeneous regions are obtained.                                                                                                                                                               | • Difficult to predict $k$ with fixed number of clusters.  
                           • Sensitive to initialization condition of cluster number and centre.  
                           • Computationally expensive.  
                           • Doesn’t works well with non globular clusters.                                                                                                                                                      |
| Method                 |                                                                                                                                                                                                             |                                                                                                                                                                                                           |
| Fuzzy C – means Method | • FCM is better than $K$-means.  
                           • FCM Unsupervised and converge very well.                                                                                                                                                               | • Sensitive to noise.  
                           • Computationally expensive.  
                           • Determination of fuzzy membership is not very easy.                                                                                                                                                 |

Table 3.1 Advantages and Disadvantages of Image Segmentation Methods

Comparative study of these methods using some standard parameters such as: spatial information, region continuity, speed, computation complexity, automaticity, noise resistance, multiple object detection and accuracy is done. Table 3.2 presents analysis of all the methods.
### Table 3.2 Comparison of Image Segmentation Methods

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Threshold based Method</th>
<th>Region based Method</th>
<th>Discontinuity based Method</th>
<th>Cluster based Method</th>
<th>Fuzzy C – means Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spatial Information</td>
<td>Ignored</td>
<td>Considered</td>
<td>Ignored</td>
<td>Considered</td>
<td>Considered</td>
</tr>
<tr>
<td>Region Continuity</td>
<td>Reasonable</td>
<td>Good</td>
<td>Reasonable</td>
<td>Reasonable</td>
<td>Good</td>
</tr>
<tr>
<td>Speed</td>
<td>Fast</td>
<td>Slow</td>
<td>Moderate</td>
<td>Fast</td>
<td>Moderate</td>
</tr>
<tr>
<td>Computation Complexity</td>
<td>Less</td>
<td>Rapid</td>
<td>Moderate</td>
<td>Rapid</td>
<td>Moderate</td>
</tr>
<tr>
<td>Automaticity</td>
<td>Semiauto</td>
<td>Semiauto</td>
<td>Interactive</td>
<td>Automatic</td>
<td>Automatic</td>
</tr>
<tr>
<td>Noise Resistance</td>
<td>Less</td>
<td>Less</td>
<td>Less</td>
<td>Moderate</td>
<td>Moderate</td>
</tr>
<tr>
<td>Multiple Object Detection</td>
<td>Poor</td>
<td>Fair</td>
<td>Poor</td>
<td>Fair</td>
<td>Fair</td>
</tr>
<tr>
<td>Accuracy</td>
<td>Moderate</td>
<td>Fine</td>
<td>Moderate</td>
<td>Moderate</td>
<td>Moderate</td>
</tr>
</tbody>
</table>

**3.4 Conclusion**

Different techniques developed for image segmentation perform well and comparable to the methods used in practice. Result of image segmentation method is dependent on many factors such as intensity, texture, image content. Hence neither the single segmentation is applicable to all type of images nor do all the segmentation methods perform well for one particular image.