Image Segmentation Methodologies

In digital image processing methods stems from two application areas: improvement of pictorial information for human interpretation; and processing of image data for storage, transmission, and interpretation for autonomous machine perception. The field of *digital image processing* refers to processing digital images by means of a digital computer. A digital image is composed of a finite number of elements, each of which has a particular location and values. These elements are called picture element, image element pels, and pixels. An image may be defined as a two-dimensional function, \( f(x, y) \), where \( x \) and \( y \) are spatial (plane) co-ordinate, and amplitude of \( f \) at any pair of co-ordinates \( (x, y) \) is called the *intensity or gray level* of the image at that point. When \( x, y \) and the amplitude values of \( f \) are all finite, discrete quantities, we call the image a *digital image*. [1]
3.1. Fundamentals of Digital Image Processing

The fundamentals of digital image processing are as follows:

**Image Acquisition**: is the first process shown in Fig. 3.1 that acquisition could be as simple as being given an image that is already in digital form? Generally, the image acquisition stage involves preprocessing, such as scaling.

**Image Enhancement**: Enhancement technique is to bring out detail that is observed, or simply to highlight certain features of interest in an image; it is one of the subjective areas of image processing.

**Image Restoration**: is an area that also deals with improving the appearance of an image. However, unlike enhancement, which is subjective, image restoration is objective, in the sense that restoration technique tends to be based on mathematical or probabilistic models of image degradation.

**Color Image Processing**: is an area that has been gaining in importance because of the significant increase in the use of digital images over the Internet. Color is used in the basic for extracting features of interest in an image.

![Diagram of digital image processing stages](image)
Wavelets: Are the foundation for representing images in various degrees of resolution.

Compression: As the name implies, deals with techniques for reducing the storage required saving an image, or the bandwidth required transmitting it. Although storage technology has improved significantly over the past decade.

Morphological processing: deals with tools for extracting image components that are useful in the representation and description of shape.

Segmentation: procedures partition an image into its constituent parts or objects. In general, autonomous segmentation is one of the most difficult tasks in digital image processing.

Representation and description: Representation is appropriate when the focus is on internal properties, such as texture or skeletal shape. In some applications, these representations complement each other. Choosing a representation is only part of the solution for transforming raw data into a form suitable for subsequent computer processing. Description, also called feature selection, deals with extracting attributes that result in some quantitative information of interest or are basic for differentiating one class of objects from another.

Recognition: is the process that assigns a label (e.g., “vehicle”) to an object based on its descriptors. [1]

Digital Image Analysis usually involves a low-level and high-level processing. In low-level analysis, the representation of an image is transformed from a numerical array of pixel intensities to a symbolic set of image primitives: edges and regions. In high-level analysis, object labels (interpretations) are assigned to these primitives, thereby providing a semantic description of the image. Image analysis techniques can be classified into two major groups: Statistical & structural, In statistical, which uses probability distribution functions of pixels and regions to characterize the image, and structural, which analyze the image in terms of organization and relationship of pixels and regions by the specified relations. Image analysis basically involves the study of feature extraction, segmentation, and classification: as shown in fig. 3.1. [1, 2]
3.2. Image Analysis Techniques

Feature Extraction
- Spatial features
- Transform features
- Edges and boundaries
- Shape feature
- Moment's
- Texture

Segmentation
- Template Matching
- Thresholding
- Boundary detection
- Clustering
- Quad-trees
- Texture Matching

Classification
- Clustering
- Statistical
- Decision trees
- Similarity Measures
- Minimum spanning trees

Fig. 3.2: Image Analysis Techniques

3.3. Image Segmentation:

Computer tries to separate objects from the image background. It is one of the most difficult tasks in DIP. A rugged segmentation procedure brings the process a long way toward successful solution of an image problem. Output of the segmentation stage is raw pixel data, constituting either the boundary of a region or all the points in the region itself. Image segmentation is defined as the process of dividing the image into different regions [3, 4]. Also it can be defined as the process of partitioning an image into some distinct regions whose characteristics such as intensity, texture, color, etc. are similar [5, 6]. Image segmentation is generally based on one of two basic properties of intensity values: discontinuity and similarity. In the first category, the approach is to partition an image based on abrupt changes in intensity, such as edges in an image. The principle approaches in the second category are based on partitioning an image into regions that are similar according to a set of predefined criteria. Thresholding, region growing, and region splitting and merging are examples of method in this category [7]. Image segmentation is an important and early processing first stage in many image analysis problems. A major problem in such applications is the determination of the number of classes actually present in an image [8]. Image segmentation approaches can be classified according to features or type of technique used [9]. This is three major groups of segmentation
techniques: region based, edge-based, or classification, which correspond to feature extracted from pixel intensities, gradient and texture.

3.4. Practical Applications: machine vision, biometric instruments, medical imaging, etc. for the purpose of detecting, recognition or tracking of an object, Remote sensing, content-based retrieval (CBR) [10, 11]. Applications of genetic algorithm for image processing extend from evolving filters or detecting edges to making complex decisions or classifying detected features. [12]

3.5. Goals of Segmentation: Its goal is to simplify or change the representation of an image into something more meaningful or easier to analyze parts of an object from a human's viewpoint [9, 13]. Robert J. et al, define: to develop an algorithm that a) identifies perceptually homogeneous regions in natural images, b) makes minimal assumptions about the scene, and d) segments conservatively, to avoid leakage of multiple objects into single regions [11]. David A. et al, suggest the goal of segmentation should be to produce regions that correspond to distinct objects in the image. [8]

The segmentation techniques are divided in to low-level & upper-level, in low-level techniques, where as a major difference between them is the level of the a priori information used in the process of segmentation. It can be improve the matching efficiency and correctness. [9, 13]

S. Chabrier, et al. presents a new method of a segmentation result by a color representation and also he shows an application of two evaluation criteria: The Zeboudj's contrast and the Rosenberger's criteria for the determination of the best fitted parameters of a segmentation method to obtain the desired level of precision.

Types of segmentation results by considering the number of detected regions:
1. Precise segmentation results.
2. Intermediate segmentation results.
3. Coarse segmentation results.

For intensity image segmentation there exists three popular approaches are namely, i) histogram ii) region growing and iii) edge detection. [14]

3.6. Segmentation Techniques:
In segmentation phase the image (such as multi-resolution, multi-spectral) were divided in to constituent parts as shown in fig. (3.2).
The existing automatic image segmentation techniques can be classified into mainly five approaches: [15, 16, 17, 18, and 19]
1. Thresholding & histogram based,
2. Edge and Boundary-based,
3. Region-based,
4. Hybrid techniques, and
5. Morphology based.
Each of these approaches has its own merits and demerits in terms of applicability, suitability, performance, computational cost, etc. [17]
Another various existing image segmentation techniques are available such as: [5] Relaxation method, spatial clustering, fuzzy set theoretic approach, fractals based approach, MRF model-based approach, etc.
Lists several Image segmentation Techniques as shown in fig (3.3) as per [2]

**Fig. 3.4:** Image Segmentation Techniques

### 3.6.1. Thresholding Techniques:
Thresholding is one of the most important approaches to image segmentation. Suppose that the gray-level histogram corresponds to an image, \( f(x, y) \), composed of light objects
on a dark background. Furthermore, suppose that the object and background pixels have gray levels grouped into two dominant modes. One obvious way to extract the objects from the background is to select a threshold $T$ that separates these modes. Then, at any point $(x, y)$ for which $f(x, y) > T$ is called an object point; otherwise, the point is called a background point. If three or more dominant modes characterize the image histogram (for example, two types of light objects on a dark background), it is sometimes possible to segment the image by multilevel thresholding. This is generally less reliable than its single-level thresholding. Great care must be taken with illumination because it plays a crucial role in establishing the shape of the histogram in the resulting image [7, 20, and 21]. Thresholding techniques are based on the assumption that adjusts pixels or classification of pixels whose value (gray level, color value, texture, etc) lies within a certain range belongs to the same class. This can obtain good segmentation of images that include only two opposite components. Since these techniques neglect all the spatial relationship information of the images, they are inefficient for images that blur or object boundaries, or multiple image component segmentation [15, 16]. In fuzzy based thresholding technique is to measure threshold the image histogram. At the output of this stage, each object of the image, represented by a set of pixels, is isolated from the rest of the scene. The purpose of this stage is that objects and background are separated into non-overlapping sets. Usually, this segmentation process is based on the image gray level histogram. In that case; the aim is to find a critical value or threshold. The presented approach does not attempt to detect a global minimum; hence, the risk of getting blocked in a local minimum is avoided. The threshold determined in this way may or may not correspond to an absolute minimum of the histogram [22]. Siddharth Manay et al, discuss the fitting a pair of Guassian curves to the image histogram and then choosing the threshold to minimize the probability of misclassification. In adaptive threshold by noting that pixel intensities near the transitions between foreground and background (edge pixels), in a smoothed image, serve as the best local thresholds. They locate such pixels by checking for large gradients and interpolate the grayscale values of these pixels to form the thresholding surface. Also he suggest to use a diffusion model that is specifically designed to spread an edge apart in order to most quickly and effectively draw out this local discriminating information. [23]
3.6.2. Boundary-Based Techniques

The subject of edge detection is very active; the raw output of standard edge detectors, for example those based on differential operators, would generally require considerable “processing” to produce unique, smooth, persistent boundaries. There are three basic types of gray level discontinuities in digital image. \([7, 20, 21]\)

3.5.2.1 Points

3.5.2.2 Lines

3.5.2.3 Edges

The most common way to look discontinuities is to run a mask through the image from left top to right bottom. This procedure involves computing the sum of products of coefficients with the gray level contained in the region encompassed by the mask. The response of the mask at any point in the image is given by

\[
R = w_1 z_1 + w_2 z_2 + w_3 z_3 + \ldots \ldots \ldots w_9 z_9 \ldots \ldots \ldots \ldots (3.1)
\]

where 'zi' is the gray level of the pixel associated with the mask, coefficient 'wi'. The response of the mask is defined with respect to its center location and computed by using eq (3.1).

3.6.2.1 Point Detection

The Detection of points in an image is straightforward in principle using the mask as shown in fig. The point is said to be detected at the location on which the mask is centered if and only if

\[ | R | \geq T \quad \ldots \ldots \ldots \ldots (3.2) \]

where, T is non-negative threshold and R is given by eq (3.1).
A mask used for detecting isolated points different from a constant background.

### 3.6.2.2 Line Detection

This is the next level of complexity. Consider the mask as shown in the figure below,

$$
\begin{array}{ccc}
-1 & -1 & -1 \\
-1 & \ 8 & -1 \\
-1 & -1 & -1 \\
\end{array}
$$

The movement of mask around the image

- a) If the first mask is moved around an image, it would respond more strongly to lines (one pixel thick) oriented horizontally
- b) If second mask is moved around the image it would respond to lines oriented vertically,
- c) If third mask is moved around the image it would respond to lines oriented $+45^0$.
- d) If fourth mask is moved around the image it would respond to lines oriented $-45^0$.

### 3.6.2.3 Edge Detection

Edge detection is often the first step in image segmentation. Image segmentation, is a field of image analysis, which is used to group pixels into regions to determine an image composition. The Edge detection is the most common approach for detecting meaningful discontinuities in the gray level. Edges may be viewpoint dependent - these are edges that may change as the viewpoint changes, and typically reflect the geometry of the scene, objects occluding one another and so on, or may be viewpoint independent - these generally reflect properties of the viewed objects such as markings and surface shape. In two dimensions, and higher, the concept of a projection has to be considered.

A typical edge might be (for instance) the border between a block of red color and a block of yellow; in contrast a line can be a small number of pixels of a different color on an otherwise unchanging background. There will be one edge on each side of the line.
Edges play a quite important role in all applications of image processing. The edges of an image hold much information in that image. The edges give the information about where objects are, what is their shape and size, and something about their texture. An edge is where the intensity of an image moves from a low value to a high value or vice versa.

There are numerous applications for edge detection, which is often used for various special effects. Digital artists use it to create dazzling image outlines. The output of an edge detector can be added back to an original image to enhance the edges. Edge detection is also used in image registration. Image registration aligns two images that may have been acquired at separate times or from different sensors. Following figure (3.4) shows the different types of edge profiles formed in image: [7, 20, and 21]

![Fig.3.5: Different edge profiles.](image)

The image edges are detected and then grouped into contours or surfaces that represent the boundaries of image objects [16]. Edge detection is an essential task in computer vision. It covers a wide range of applications, from segmentation to pattern matching. It reduces the complexity of the image allowing more closely algorithm like object recognition, object matching, and object registration, to be used [24]. In edge detection, different approaches have been followed, such as mathematical morphology, markov random fields, and surface models. The most common method is still the derivative approach with linear filtering. Many derivative filters have been studied and used to compute the intensity gradient of gray-level images:

1. Robert, Sobel, or Prewitt operators.
2. Canny filters.
3. First-order recursive known as exponential or Shen filter.
5. First derivative of the Guassian function. [25]

Criteria of edge detection quality: one's that are best defined are based on Canny's theory: good detection, good localization, and low multiplicity of the response to a single-step
edge. Many successful improvements made to adopt canny criteria in order to enable the
detection of roofs or ramp edges or to include a resolution hypothesis. One of the major
drawbacks of these criteria is that they only work on the domain of continuous signals.
The fact that canny imposes continuity of the impulse response in its center is also
unsatisfying. [16, 25]
Recently, progress is in research by using Gaussian mixture models on image
segmentation. The main disadvantage of this model is that the number of Gaussian
mixture components (K) has to be assumed and hence these algorithms cannot be
considered as totally unsupervised image segmentation. Wu, has suggest that K-means
for solving the initialization of model parameters. The K-means algorithm can be run
multiple times to reduce this effect. To overcome this problem by using the hierarchical
clustering segmentation algorithm has been used. [4]
Use the assumption that pixel values change rapidly at the boundary between two
regions. Edge detectors used in these techniques can be simple ones such as the Sobel or
Robert operators, or more complex ones such as the canny operator. The output of most
of existing edge detector techniques can only provide candidates for the region
boundaries, because these obtained color edges are normally discontinues or over-
detected. However the actual region boundaries should be closed curves. Therefore, some
post-processing, such as edge tracking, gap filling, smoothing, and thinning, should be
performed to obtain the closed region boundaries. All of these post processing's very time
consuming; converting the edge candidates to the region boundaries in thus not an easy
task. This can be avoided by integrating the results of the boundary-based approach and
those of the region-based approach. [15]

The Edge detection is the most common approach for detecting meaningful
discontinuities in the gray level. The edges give the information about where objects are,
what is their shape and size, and something about their texture. An edge is where the
intensity of an image moves from a low value to a high value or vice versa.
In this technique, we use different types of edge detection operators, such as prewitt,
canny, sobel, Robert, log, zero-cross, etc. & to use a default threshold 0.1 as shown in
table 3.1 and also to count the number of objects before and after. Log edge detection
refers to laplacian method of edge detection has 0.1 as default threshold. Zero cross edge

55
detection method also has the default 0.1 threshold. By using this threshold different results will be appeared. Only prewitt and sobel operator gives good results, spots edges will be separately findout as compare to other canny, Robert, log and zero-cross. By using log and zero-cross spots edges will be merged together.

Table: 3.1: Edge Detection using constant threshold (0.1), different operators and objectcount.

<table>
<thead>
<tr>
<th>Operator</th>
<th>Threshold</th>
<th>No. of objects before</th>
<th>No. of objects after</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prewitt</td>
<td>0.1</td>
<td>342</td>
<td>2915</td>
</tr>
<tr>
<td>Canny</td>
<td>0.1</td>
<td>342</td>
<td>2299</td>
</tr>
<tr>
<td>Sobel</td>
<td>0.1</td>
<td>342</td>
<td>2812</td>
</tr>
<tr>
<td>Robert</td>
<td>0.1</td>
<td>342</td>
<td>1260</td>
</tr>
<tr>
<td>Log</td>
<td>0.1</td>
<td>342</td>
<td>2155</td>
</tr>
<tr>
<td>Zero-cross</td>
<td>0.1</td>
<td>342</td>
<td>2155</td>
</tr>
</tbody>
</table>

Fig. 3.6: Edge Detection by prewitt operator
Fig. 3.7: Edge Detection by canny operator

Fig. 3.8: Edge Detection by sobel operator
Fig. 3.9: Edge Detection by Roberts operator

Fig. 3.10: Edge Detection by log operator
3.6.3. Region-Based Techniques:

The objective of the segmentation is to partition an image into regions (segmentation as a process that partitions R into n subregions, R1, R2,…Rn). The basic formulations are for regions [7, 20] as

\[(a) \bigcup_{i=1}^{n} R_i = R\]

\[(b) R_i \text{ is connected Region, } i = 1, 2, \ldots, n\]

\[(c) R_i \cap R_j = \emptyset \text{ for all } i \text{ and } j, i \neq j. \quad \text{…………(3.3)}\]

\[(d) P(R_i) = \text{True} \text{ for } i = 1, 2, \ldots, n.\]

\[(e) P(R_i \bigcup R_j) = \text{False}, \text{ For } i \neq j\]

Here, P(Ri) is the logical predicate defined over the points in the set Ri and Ø is the null set, the condition (a) in eq (3.3) indicates that the segmentation must be complete that is every pixel must be in region, (b) in eq (3.3) indicates that point in the region must be connected in some predefined sense, (c) in eq (3.3) indicates that the regions must be disjoints, (d) in eq (3.3) indicates that, this deals with the properties that must be satisfied by the pixel in a segmented region that is P(Ri)=TRUE if all pixel in Ri have the same
gray level where as (e) in eq (3.3) indicates that the region Ri and Rj are different in the
sense of predicate P [7, 20].

3.6.3.1 Region Splitting and Merging Using Quadtree:

This is an alternative method to subdivide an image initially into set of arbitrary, disjoined regions and then merge and/or split the regions in an attempt to satisfy the conditions for region formation as per eq (3.3). By splitting and merging algorithm that iteratively works towards satisfying these constrains of similarity.

Let R represents the entire image region and selects the predicate P. One approach for segmenting R is to subdivide it successively into smaller and smaller quadrant regions so that for any region Rₖ, P(Rₖ) = TRUE. Hence start with the entire region. If P(R) = FALSE, divide the image into quadrants. If P is FALSE for any quadrant, subdivide that quadrant into sub quadrants, and so on. These particular splitting techniques that has a convenient representation in the form of a so called quadtree as shown in figure 3.3. Note that the root of the tree correspond to the entire image and that each node correspond to a subdivision. In this case, only R₄ was subdivided further as shown in fig. 3.5. This drawback may be remedied by allowing merging, as well as splitting. [7, 20]

![Quadtree Diagram](image)

**Algorithm:**

1. Split into four disjoint quadrants any region Rᵢ for which P(Rᵢ) = FALSE.
2. Merge any adjacent regions Rᵢ and Rₖ for which, P(Rᵢ U Rₖ) = TRUE.
3. Stop when no further merging or splitting is possible.

The goal is the detection of regions (connected set of pixels) that satisfy certain predefined homogeneity criteria [16] or really on the assumption that adjacent pixels in the same region have similar visual features such as gray level, color value, or texture. A
well known of this approach is split and merge. Obviously, the performance of this approach largely depends on the selected homogeneity criterion [15, 16]. Instead of tuning homogeneity [19] parameters, the seed region growing (SRG) technique is controlled by a number of initial seeds. Given the seeds, SRG tries to find an accurate segmentation of images into regions with the property that each connected component of a region meets exactly one of the seeds. Forever, high-level knowledge of the image components can be exploited through the choice of seeds. This property is very attractive for semantic object extraction toward content-based image database applications. SRG suffers from another problem: how to select the initial seeds automatically for providing more accurate segmentation of images. In splitting techniques, the entire image is initially considered as one rectangular region. In each step, each heterogeneous image region of the image is divided into four rectangular segments and the process is terminated when all regions are homogeneous. In split-and-merge techniques, after the splitting stage a merging process is applied for unifying the resulting similar neighboring regions. The splitting technique tends to produce boundaries consisting of long horizontal and vertical segments [15, 16]. Shu-Yen Wan et al. has proposed new Symmetric region growing (SymRG) technique. A symmetric region-growing algorithm can initiate the segmentation process anywhere within an image. The seed criteria used to identify the final regions of interest can be applied later. Such type of technique is Split/Merge approach; it can be provided that all of the splitting and merging criteria are symmetric function. Also both are computation and memory efficient [26]. It consists of two basic steps. First the whole image considered is considered as one region. If this region does not satisfy homogeneity criteria the region is split into four quadrants and each quadrant is tested in the same way; this process is recursively repeated until every square region created in this way contains homogeneous pixels. In second step, all adjacent regions with similar attributes may be merged in other criteria. [19]

This is an alternative method to subdivide an image initially into set of arbitrary, disjointed regions and then merge and/or split the regions in an attempt to satisfy the conditions for region formation as per equation 3.3. The edge detection is an important issue for complete understanding of image. Quadtree is an image segmentation method basically used for region splitting and merging; based on the criteria of similarity were it
prepares the segment by applying the predicate (Threshold) on image by using this technique image results will be poor the presented statistical results mean and STD also gave poor results as shown in table 3.2.

Fig. 3.13: Micro original
Fig. 3.14: Micro Resultant
Fig. 3.15: Micro1 original
Fig. 3.16: Micro1 Resultant
Fig. 3.17: Micro3 Original
Fig. 3.18: Micro3 Resultant
Fig. 3.19: Micro4 original

Fig. 3.20: Micro4 Resultant

Fig. 3.21: Micro5 Original

Fig. 3.22: Micro5 Resultant

Fig. 3.23: Micro6 Original

Fig. 3.24: Micro6 Resultant

Fig. 3.25: Micro7 Original

Fig. 3.26: Micro7 Resultant
Fig. 3.27: Micro8 Original

Fig. 3.28: Micro8 Resultant

Fig. 3.29: Micro9 Original

Fig. 3.30: Micro9 Resultant

Fig. 3.31: Micro10 Original

Fig. 3.32: Micro10 Resultant

Table 3.2: Quadtree decomposition using constant Threshold 0.27:

<table>
<thead>
<tr>
<th>Image</th>
<th>Mean Before</th>
<th>Mean After</th>
<th>STD Before</th>
<th>STD After</th>
</tr>
</thead>
<tbody>
<tr>
<td>Micro</td>
<td>117.3471</td>
<td>161.0817</td>
<td>127.0961</td>
<td>122.999</td>
</tr>
<tr>
<td>Micro1</td>
<td>140.9771</td>
<td>171.9514</td>
<td>126.7867</td>
<td>119.5012</td>
</tr>
<tr>
<td>Micro3</td>
<td>93.2258</td>
<td>146.0637</td>
<td>125.4684</td>
<td>115.1546</td>
</tr>
<tr>
<td>Micro4</td>
<td>150.1751</td>
<td>182.2346</td>
<td>127.0379</td>
<td>124.4449</td>
</tr>
<tr>
<td>Micro5</td>
<td>138.3567</td>
<td>155.2478</td>
<td>114.1405</td>
<td>123.4473</td>
</tr>
<tr>
<td>Micro6</td>
<td>70.6811</td>
<td>159.3944</td>
<td>120.728</td>
<td>127.4937</td>
</tr>
<tr>
<td>Micro7</td>
<td>86.4974</td>
<td>126.1333</td>
<td>125.3985</td>
<td>98.0441</td>
</tr>
<tr>
<td>Micro8</td>
<td>104.4416</td>
<td>209.0092</td>
<td>122.0662</td>
<td>126.6254</td>
</tr>
<tr>
<td>Micro9</td>
<td>90.6717</td>
<td>112.5837</td>
<td>127.4979</td>
<td>127.1908</td>
</tr>
<tr>
<td>Micro10</td>
<td>128.3798</td>
<td>136.3877</td>
<td>127.1908</td>
<td>127.1908</td>
</tr>
</tbody>
</table>
3.6.4. Hybrid Techniques: Most of them are based on the integration of edge-and region-based methods. Which integrates the result of boundary detection and region growing, are expected to provide more accurate segmentation of images? Palvidis et al. suggest that a method to combine segments obtained by using a region-growing approach, where the edge between regions are eliminated or modified based on contrast, gradient and shape of the boundary. Hadden and Boyce generate regions by partitioning the image co-occurrence matrix and then refining them by relaxation using the edge maps obtained from several channels, including visible, infrared, etc. where user specified weights and arbitrary mixing of region and edge maps are allowed [15]. Edge and region-based techniques through the morphological watershed transform are one of the examples of hybrid technique. [16]

The main advantages of watershed method as compare to previous technique:
1. The resulting boundaries from closed and connected regions. Traditional edge based techniques most often from disconnected boundaries that need post-processing to produce closed regions.
2. The boundaries of the resulting regions always correspond to contours, which appear in the image as obvious contours of object. This is in contrast to split and merge method where the first splitting is often a simple regular sectioning of the image leading sometimes to unstable results.
3. The union of all the regions from the entire image region. [10]

3.6.5. Morphology Based Techniques:
Mathematical morphology uses set transformations for image analysis. It extracts the impact of a particular shape on images via the concept of structuring element. Different standard morphological operations are namely dilation, erosion, opening, closing, etc. The shape and size of the structuring element plays an important role in detecting or extracting features of given shape and size from the image [17]. Also it encodes the primitives shape information. During morphological operations, the center scans the whole image and the matching shape information is used to define the transformation. The morphological operations are generally simple to understand and implement. At the same time, these are difficult to control. This algorithm requires some external criteria to
control them. These operations also have a risk of changing the morphology of the input datasets. [27]

3.7. Other Existing Image Segmentation Techniques:

3.7.1 Texture Based Segmentation:
The process of finding region boundaries based on texture properties is known as texture-based segmentation. When a digital image contains regions of distinctly different texture, it is possible to segment the image into its component parts based on texture. In order to perform image segmentation efficiently, it is necessary to develop compact mathematical measures or rules for texture description or characterization. There are many types of texture features already exist. Textures features based on gray-level run length statistics, texton gradients, fractal dimension, morphological filters, Fourier filters, Gabor filters, and random field models are used. Another association rule features perform well for supervised segmentation problems. Simulation results using images with texture regions of various shapes and sizes indicate that association rule features achieve segmentation accuracy comparable to that achieved using GLCM (Gray level co-occurrence matrix) features [28]. Robert J. et al, discuss the texture watershed, current method follows the approach of, which integrates a measure of spatial variation in texture with the traditional intensity gradient. This so-called "texture watershed" consists of a number of conceptual stages. [11]

1. Compute a texture representation that characterizes a local area surrounding each pixel.
2. Post process the texture features to make them suitable for meaningful gradient extraction.
3. Generate gradient images for each of the texture feature, as well as grayscale intensity and potentially color.
4. Normalize the contribution of each gradient image.
5. Combine the various gradient images to form the single valued gradient surface.
6. Segment by applying the watershed transform to this surface.

3.7.2 Color Image Segmentation: color of an image can carry much more information than gray level. It can be divided into the following categories: Statistical approaches, edge detection, region splitting and merging approaches, methods based on physical reflectance models, methods based on human color perception, and the
approaches using fuzzy set theory [29]. It can be classified into four types such as 1. Histogram based, 2. Neighborhood based, 3. Clustering based, 4. Hybrid based approaches. [30]

Histogram is a popular that looks for the peaks and valleys in histogram. The major advantage of this method lies in its simple computation.

Neighborhood based approach usually uses the uniformity criteria to segment regions in the image. e.g. region based techniques.

Clustering based approach generally uses a fuzzy logic to define membership of the pixels. e.g. fuzzy C-means (FCM) algorithm.

Hybrid based approach improve the segmentation result by combining all above methods for segmentation. e.g. watershed and region merging.

3.7.3 Genetic Algorithm: genetic algorithm is the most powerful unbiased optimization techniques for sampling a large solution space. This explains the increasing popularity of genetic algorithm applications in image processing and other fields. They were quickly adapted in image processing stages, for the image enhancement, segmentation, feature extraction and classification as well as the image generation. To solve optimization problems using genetic algorithm is a primary optimization tool. The field of genetic algorithms applications is growing fast. The contrast improvement of genetic algorithms will definitely help to solve various complex image-processing tasks in the future. [12]

3.7.4 Fuzzy Image Segmentation: Faguo Yang et al, propose a new pixon definition scheme that is more suitable for image segmentation that the “fuzzy” pixon definition scheme. The anisotropic diffusion equation is successfully used to from the pixon in their pixon definition scheme. By incorporating the pixon concept into their pixon method, the computational cost has been deceased greatly compared to traditional MRFs-based model. [6] I. Lizarazo et al, has proposed fuzzy image segmentation. This method is the following advantages compared to the object-oriented classification using commercial software: simplicity, flexibility, and low cost [31].

3.7.5 Clustering Based Segmentation: cluster analysis is a branch in statistical multivariate analysis and an unsupervised learning in pattern recognition. It is a method for clustering a data set into most similar groups in the same cluster and most dissimilar groups in different clusters. The clustering categories can be classified: hierarchical
clustering, mixture model clustering, linear-network clustering, objective-function based clustering, and partition clustering. Most of these methods are less to include the property of robustness. A robust idea is important in pattern recognition. Robustness involves three aspects: 1. Robust to the initialization, 2. Robust to cluster volumes, 3. Robustness to noise and outliers. [32]

Xiang-Ping Zhang et al, has proposed a new method for the segmentation of bright targets in an image. Wavelet transforms are used in the new method and the Bayes classifier is employed for the segmentation problem. An approach for choosing the threshold adaptively by looking for the global local minima of the PDF’s of wavelet-transformed images is proposed. [33]

Tianhu Lei et al, discuss the probability distribution function (PDF) of the entire image is weighted summation of the individual Gaussian PDFs. This stochastic model is known as finite normal mixture (FNM). The task of image segmentation based on a FNM model can be divided into three steps: 1. Detecting the number of image regions. 2. Estimating the FNM model parameters and 3. Classifying the pixels is into the different image regions. These three operations are implemented by using i) theoretical information criteria, ii) Expectation-Maximization (EM) or Classification-Maximization (CM) algorithm, and iii) Bayesian classifier, respectively. [2]

Faguo Yang et al, discusses the Markov random fields (MRF)-based model is a great importance for their ability to model a prior belief about the continuity of image features such as region labels, textures, edges. Image interpretation, which is transformed into an optimization problem in MRF-based method, is depends on both the observed image and some prior beliefs of the image [6]. Most of previous image segmentation techniques are statistical techniques in which the image classes, or region states, are characterized by various low-order statistical measures, such as mean, variance, and correlation functions or power spectral densities, etc. [8]. John M. Gauch, et al, has focused on the multiscale properties of watershed boundaries and gradient watershed boundaries for an image. The three main advantages of this approach are as follows.

1. Multiscale analysis of watershed regions is fast and easy. There is one-to-one relationship between intensity extrema and watershed regions in the image. By exploiting this relationship, we can build hierarchies on watershed regions by simply following
intensity extrema through scale-space and detecting their annihilations. This is much easier than following curve segments associated with edges or ridge tops through multiple scales and imposing a scale-based hierarchy on these structures.

2. He can associate visually sensible measurements of importance to individual curve segments, which make up the boundaries of watershed regions. For images with ridge-like marks the top of ridges. For gradient magnitude images, these curve segments correspond to edges of objects in the original image. Thus, multiscale watershed analysis can be used indirectly as an edge detection method.

3. Interactive image segmentation tools can be constructed which use gradient watershed region hierarchies to quickly and easily identify image regions associated with objects of interest. The use of region painting and hierarchy traversal are general methods that could be used with any region hierarchy of visually sensible regions.

The multiscale watershed analysis provides an alternative method to study the scale-space behavior of ridges and valleys in an image. One advantage of this approach is that no new intensity extrema are created as scale is increased. The mathematical morphology scale space approach remains computationally demanding. [34]

3.8. Problems of Existing General Image Segmentation Techniques: The objective function associated with most nontrivial MRF problems is extremely nonconvex, which makes the corresponding minimization problem very time consuming [6]. A gradient thresholding suffers from a problem of yielding contours with nonuniform thickness as well as discontinuities due to difficulty in selecting optimum threshold. The watershed algorithm, morphological instance of region-based approach apart from being computationally intensive, suffers from over segmentation [11, 17]. John M. Gauch et al has mentioned one of the problems from their methods is the difficulty of retaining connected edge segments through scale-space. A second difficulty is constructing object regions from these boundaries. [34] Statistical analysis of the correlation between features of a part and tracking error, identifying a cost function that exhibits a higher degree of correlation with the tracking error than other indicators previously proposed, and a segmentation algorithm specifically designed to make optimal use of the spatial information available to improve tracking robustness. This segmentation is obtained by combining this new cost function with the standard active contours frameworks [35].
How to define an MRF that is able to keep into account prior information while remaining mathematically and numerically manageable; how to set or estimate the numerical parameters of such an MRF; how to solve the maximum a posteriori probability (MAP) estimation problem with reasonable computational complexity [36]. Ronald Wilson et al, has address two problems which are important in a number of applications: images may contain an unknown number of classes and regions within which there is significant variation of properties, such as intensity and texture [37].

3.9. Image Registration: Due to the development of acquisition devices the diversity of applications for image registration has grown significantly. The various image registration methods were used are computer aided diagnosis, atlas construction, computer vision, remote sensing, cartography, etc. The basic process of image registration is transformation, similarity measure, and optimization algorithm, etc. the transformation is a class of geometric transformation, which explains how do we actually overlay one image onto the other. The similarity measure is also known as alignment measure, registration function etc., or more general, energy function, cost function or score. It quantifies the similarity between two images. The optimization algorithm explains how to find the similarity measure maximum. The different approaches for classification of image registration methods are proposed in different criteria's: technical requirements, nature of distortion and methodology. All three criteria are heavily coupled since nature of distortion narrows down the choice of methodology while requirements place additional restrictions. Therefore, the different technical requirements that can be put on the image registration methodology, and according to which we may divide image registration techniques are: speed, dimensionality, and interaction. [9]

The registration of images acquired by scene changed usually makes scene only if the subject remains unchanged. This classification can be listed as:

1) Subject:
   Inter-subject
   Intra-subject
   Model. [9]
2) Scene:
   Multimodality
Finally, he classifies the image registration techniques according to the methodologies used.

1) Transformation
   a. Rigid
   b. Curved

2) Similarity Measure
   a. Intensity Based
      Pixel intensity method
      Correlation like method
      Entropy like method
   b. Landmark based.
      i. Extrinsic
      ii. Intrinsic
         Anatomical
         Geometrical

3) Optimization algorithm
   Deterministic
   Heuristic
   Or
   Constrained
   Unconstrained. [9]

3.10. Classification of Image Quality Measure:
Table 3.3 shows the recently published author has been mention image quality measures. Measures that require both the original image and distorted image are called "full-reference" or "blind" methods, and measures that require both the distorted image and partial information about the original image are called "reduced-reference" method. [38]
Table: 3.3: Classification of image quality measure: [38]

<table>
<thead>
<tr>
<th>Author</th>
<th>Domain type</th>
<th>Type of distribution predicted</th>
<th>Type of information needed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Van der Weken, Nachtegael and Kerre, 2003</td>
<td>Pixel</td>
<td>Salt and popper noise, enlightening and darkening</td>
<td>Full-reference</td>
</tr>
<tr>
<td>Bovik and Liu, 2001</td>
<td>Discrete Cosine Transform</td>
<td>JPEG compression</td>
<td>No-reference</td>
</tr>
<tr>
<td>Wang, Bovik and Evans, 2000</td>
<td>Pixel</td>
<td>JPEG compression</td>
<td>No-reference</td>
</tr>
<tr>
<td>Wang, and Bovik, 2002</td>
<td>Pixel</td>
<td>JPEG compression</td>
<td>No-reference</td>
</tr>
<tr>
<td>Ong, Lin, Lu, Yang, Yao, Pan, Jiang and Moschetti, 2003</td>
<td>Pixel</td>
<td>Guassian blur, JPEG 2000 compression</td>
<td>No-reference</td>
</tr>
<tr>
<td>Meesters and Martens, 2002</td>
<td>Pixel</td>
<td>JPEG compression</td>
<td>No-reference</td>
</tr>
<tr>
<td>Carnec, Le Callet and Barba, 2003</td>
<td>Pixel</td>
<td>JPEG &amp; JPEG 2000 compression</td>
<td>Reduced-reference</td>
</tr>
</tbody>
</table>

Ratchakit Sakuldee, et al, suggests that measurement of image quality can be categorized into two types: subjective (MOS) & objective quality measure. Objective measurements are developed such as MSE, MAE, PSNR, SC, MD, LMSE, and NAE that are least time taken than MOS but they do not correlation well with subjective quality measures. MSE & PSNR are the most common measure of image compression systems. [39]
Aleksandr Shnayderman, et al, discuss a new image quality measure that can be used graphically as a two-dimensional tool or numerically as a scalar metric. The numerical measure is expressed as a Minkowski metric. It computes a global estimate of the distortion in the image. The graphical measure consistently displays the type and amount of distortion as well as the distribution of error in all the images. Aleksandr used a wide range of distortion types including compression, blur, noise, sharpening and DC-shifting. [40] An ideal image quality measure should be able to describe:

1. The amount of distortion,
2. The type of distortion, and
3. The distribution of error. [40, 41, 42, 43]

Ahmet M. Eskicioglu, have been classify image quality criteria subjective and quantitative is shown in the given Table 3.4. [41]

**Table: 3.4: Classification of image quality measure: [38]**

<table>
<thead>
<tr>
<th>Subjective</th>
<th>Quantitative</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absolute computative</td>
<td>Numerical</td>
</tr>
<tr>
<td></td>
<td>MSE</td>
</tr>
<tr>
<td></td>
<td>Lp-norm</td>
</tr>
<tr>
<td></td>
<td>Power spectrum</td>
</tr>
<tr>
<td></td>
<td>Other</td>
</tr>
</tbody>
</table>

In many cases, subjective rating results may not be reproducible as they can be affected by a number of factors including:

a) Type, size and range of motivation,

b) Observers background and motivation,

c) Experimental conditions (lighting, display quality, etc.)

Quantitative measures for image quality can be classified according to two criteria:

1) The number of images used in the measurement;

2) The nature of type of measurement. [41]
3.11. Summary: In this chapter we have mentioned details about various existing image segmentation methodologies and our applied technique, which is considering different approaches together at different levels. Mainly the edge detection & Quadtree decomposition techniques applied in microarray images but such method were not found useful to microarray images due to too minute size. And different types of edge detections technique and different types of edge detection operators, such as prewitt, canny, sobel, Robert, log, zero-cross, etc. with a default threshold 0.1 which was found suitable for our experiment after lot of trials, we used them to count the number of objects before and after. Log & Zerocross edge detection method even showed better results with the default 0.1 thresholds. By using this threshold different results were observed for further processing. But prewitt and sobel operator gave better results compared to the above techniques mentioned, here the spots edges separately found as compare to other canny, Robert, log and zero-cross. To split the merge spots we tried with log and zero-cross spots edge which didn’t yield satisfactory result thus in the next stage we tried with morphological analysis which is discussed in the next chapter.

References:
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[31] I. Lizarazo, J Barros, "Fuzzy Image Segmentation for urban land-cover classification", 76
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