Chapter 3: Color Image Segmentation Techniques

"Science may limits to knowledge, but should not set limits to imagination."

Bertrand Rusell
3.1 Introduction

Previous chapter discusses about the color theory and different color space transformation models. This chapter is an endeavor to review various algorithms and recent advances in color image segmentation. Image segmentation entails the division or separation of images into regions of similar attribute [1]. It is a key aspect of the human visual perception. Humans use their visual sense effortlessly to partition their surrounding environment into different objects to help recognize them, guide their movements and for almost every other task in their lives. It is a multifarious process that includes many interacting components which are involved with the analysis of color, shape, motion and texture of objects within an image. Haralick and Shapiro have established the following qualitative guideline for a good image segmentation [2]: (1) Regions of an image segmentation should be uniform and homogeneous with respect to some characteristic such as gray tone or texture. (2) Region interiors should be simple and without many small holes. (3) Adjacent regions of segmentation should have significant different values with respect to the characteristic on which they are uniform. (4) Boundaries of each segment should be simple, not ragged and must be spatially accurate. Fu and Mui defined image segmentation to be a psychophysical problem and therefore not simply a subject of analytical solutions [3].

Emerging applications, such as multimedia databases, digital photography and web-based visual data processing generated a renewed interest on image segmentation, so that the field has become an active area of research not only in engineering and computer science but also in other academic disciplines, such as geography, medical imaging, criminal justice, computer based training, video conferencing and telemedicine, remote sensing with the development of hardware and communication infrastructure to support visual applications [4]. Many reasons can be cited for the success of the field. There is a strong underlying analytical framework based on mathematics, statistics and physics. Thus, well founded, robust algorithms that eventually lead to consumer applications can be designed. The field has also been helped tremendously by the advances in computer and memory technology, enabling faster processing of images, as well as in scanning and display.
A major attention in image segmentation has been focused on gray scale image segmentation [5]. A common problem in segmentation of monochrome image occurs when regions assume some broad range of gray-levels. It is well known that the human eye can detect only in the neighbourhood of one or two dozen intensity levels at any point in a complex image due to brightness adaptation. However, it can differentiate thousands of color shades easily. Of course, the visual experience of the normal human eye is not limited to gray scales. Color is an extremely important aspect of images [6]. It is also an important aspect of digital image. This chapter surveys the existing techniques of color image segmentation. The methods are reviewed in six major classes as:

1. Pixel-based techniques
2. Edge-based techniques
3. Region-based approach
4. Fuzzy-based approach
5. Neural network based approach
6. Hybrid based techniques.

The rest of the chapter is structured as follows: Section 3.2 to 3.7 elaborates the different techniques for color image segmentation, their complexity, advantages and disadvantages. Several generic algorithms of image segmentation are described in subsequent section. The final section concludes with summary.

3.2 Pixel-based techniques

Pixel-based techniques do not consider the spatial context but decide solely on the basis of color features at individual pixels. This attributes has its advantages and disadvantages. Simplicity of the algorithm is an advantage to pixel-based techniques while lacks of spatial constraints makes them susceptible to noise within images [7]. It is categorized into histogram thresholding and clustering methods.

3.2.1 Histogram thresholding

The simplest technique of pixel-based segmentation is histogram thresholding. Image histogram displays the number of pixels at each gray scale value within an image or region. It is useful in image processing applications such as image compression, segmentation etc. Image histogram is simple to calculate in software and also lend
themselves to economic hardware implementations thus making them a popular tool for real time image processing.

Histogram thresholding is one of the oldest and widely used techniques for image segmentation [8]. If an image is composed of distinct regions, the histogram of image usually shows different peaks, each corresponding to one region and adjacent peaks are likely to be separated by a valley. For example, if the image has a distinct object on a background, the histogram is likely to be bimodal with a deep valley. In such a case, the bottom of the valley is taken as a threshold so that the pixels that belong above and below this value on histogram are grouped into different regions. Complete segmentation can result from thresholding in simple scenes. Thresholding is the transformation of an input image $f$ to an output (segmented) binary image $g$ as follows [9]:

$$
\begin{align*}
g(i, j) &= 1 \text{ for } f(i, j) \geq T \\
g(i, j) &= 0 \text{ for } f(i, j) < T
\end{align*}
$$

Where $T$ is the threshold, $g(i,j)=1$ for image elements of objects, and $g(i,j)=0$ for image elements of the background (or vice versa). The basic thresholding algorithm is described below.

**Algorithm: Basic thresholding**

Search all the pixels $f[i,j]$ of the image $f$, where an image element $g(i,j)$ of the segmented image is an object pixel if $f(i,j) \geq T$ and is a background pixel otherwise.

Correct threshold selection is crucial in order to carry out successful threshold segmentation. Thresholding can also be done based on global information (e.g. gray level histogram of the entire image) or using local information (e.g. co-occurrence matrix) of the image [10]. Under each of these schemes if only one threshold is used for the entire image, it is known as global thresholding. On the other hand, when an image is partitioned into several sub regions and a threshold is determined for each of the sub regions, it is referred to as local thresholding. A novel system for color image segmentation using localized histogram is presented [11]. The proposed technique uses a local window image histogram which is easy to compute and could quickly collect the information of neighbors, together with a neural network. The number of thresholds which are used to detect clusters and their labels are found automatically from the first...
order derivative of smoothed histogram in HSV color space. The advantage of this method is that no \textit{a priori} information is required to segment the color image. The significant use of local information improves the quality of segmentation result.

Thresholding techniques can also be classified as bi-level thresholding and multithresholding [12]. In bi-level thresholding the image is partitioned into two regions, object (black) and background (white). One obvious way to extract objects from the background is to select a threshold $T$ that separates these modes. Then any point $(x,y)$ for which $f(x,y)>T$ is called an object point; otherwise the point is called a background point. When an image is composed of several objects with different surface characteristics one needs several thresholds for segmentation. This type of thresholding is known as multithresholding. There are various methods available to find out multiple thresholds for segmentation. Otsu maximized a measure of class separability. He maximized the ratio between class variance to the local variance to obtain thresholds [8]. Nakagawa and Rosenfeld assumed that the object and background populations are distributed normally with distinct means and standard deviations [15]. Under this assumption they selected a threshold by minimizing the total misclassification error. Pal and Pal modeled an image as a mixture of two Poisson distributions and developed several parametric methods for segmentation [7]. The assumption of Poisson distribution has been justified based on the theory of image formation. These algorithms maximize either entropy or minimize statistic. Though this method uses histogram, they produce good results due to incorporation of the image formation model.

An adaptive neuro-fuzzy system for image segmentation proposed in [13]. It is based on multilevel histogram thresholding technique. The proposed system consists of multilayer perceptron (MLP) like network which performs image segmentation. Threshold values for detecting clusters and their labels are found automatically using FCM clustering technique. Fuzzy entropy is used as a tool to decide number of clusters. Neural network is employed to find out the number of objects automatically from an image. One of the advantages of this method is that it does not require \textit{a priori} knowledge about the number of regions within an image.

A color image segmentation technique based on histogram thresholding is proposed in [14]. This technique attempts to detect the peaks of three histograms in hue, value and
chroma (HVC) components of Munsell color space. All these methods have a common drawback; they take into account only the histogram information (ignoring the spatial details). As a result, such an algorithm may fail to detect thresholds if these are not properly reflected as valleys in histogram which is normally the case [16].

3.2.2 Clustering

Clustering is a pixel-based technique that is extensively used for image segmentation. The rationale behind clustering technique is that typically, the colors in an image tend to form clusters in the histogram, one for each object [17]. In this method, first cluster centers are obtained using color values of all pixels. In the next phase, each pixel is assigned to one of the clusters that it is closest to the pixel color. Many different clustering algorithms are in existence today. Among these, K-means and the fuzzy K-means algorithms have received extensive attention [18].

A color image segmentation algorithm based on fuzzy homogeneity is proposed [19]. Fuzzy set theory and maximum fuzzy entropy principle are used to map the color image from space domain to fuzzy domain, which keeps the maximum information. Both the global and local information is taken into account while calculating the fuzzy homogeneity histogram. The scale space filter (SSF) is utilized to analyze the homogeneity histogram to find out the appropriate number of segments. The final result is transformed from fuzzy domain to space domain using inverse S-function.

Clustering techniques can be combined with histogram thresholding approaches. Tominaga proposed a new method for clustering using histogram thresholding that uses three perceptual attributes [14,20]. The method consists of two steps. The first step is a modification of the algorithm for using three perceptual attributes [14]. The modification consists of computing the principal component axes in the CIE L*a*b* color space for every region to be segmented. In other words, the color features have been transformed onto the principal component axes. Peaks and valleys are searched within three 1-D histograms of the coordinate axes. The second step is a reclassification of pixels based on a color distance measure. Suppose a set of K representative colors \( \{m_1, m_2, ..., m_K\} \) are extracted from an image; the first cluster center \( a_1 \) in the color space is chosen as \( a_1 = m_1 \). Next, the color difference from \( m_2 \) to \( a_1 \) is computed. If this difference exceeds a given
threshold $T$, a new cluster center $a_2$ is created as $a_2 = m_2$. Otherwise $m_2$ is assigned to the domain of the class $a_1$. In a similar fashion, the color difference from each representative color $\{m_1, m_2, \ldots, m_K\}$ to every established cluster center is computed and thresholded. A new cluster is created if all these distances exceed $T$; otherwise the color is assigned to the class to which it is closest.

In summary, the pixel-based segmentation techniques surveyed in this section do not consider the spatial constraints which make them susceptible to noise within images. The resulting segmentation often contains isolated, small regions that are not present in noise-free images.

3.3 Region-based techniques

Region-based techniques focus on the continuity of a region within an image. Segmenting an image into regions is directly accomplished through region-based segmentation which makes it one of the most popular technique used today [21]. Unlike the pixel-based technique, region-based approach considers both the color distribution in color space and the spatial constraints. Standard region based technique include region growing, region adjacency graph and split and merge techniques.

3.3.1 Region growing

A region growing algorithm typically starts with a seed pixel. The region grows by iteratively adding unassigned neighboring pixels that satisfy some homogeneity criterion with the existing region of the seed pixel. Several homogeneity criterions linked to color similarity or spatial similarity can be used to analyze if a pixel belongs to a region. The selection of similarity criterion depends not only on the problem under consideration, but also on the type of image data available. For example, the analysis of land-use satellite imagery depends heavily on the use of color. This problem would be significantly more difficult, or even impossible to handle without inherent information available in color images.

The important issues considered for region growing algorithms are as follows [22]:

- Selection of an initial seeds that represents regions and the selection of suitable properties for including the points in various regions during the growing process.
Growing pixels based upon certain properties of image may not ascertain good segmentation. Connectivity or adjacency information should also be used in region-growing process.

Similarity: The similarity denotes the minimum difference in gray level or color observed between two spatially adjacent pixels or average gray level of a set of pixels which will yield different regions. If this difference is less than the similarity threshold value, the pixels belong to the same region.

Area of region: The minimum area threshold is associated with the smallest region size in pixels. In the segmented image, no region will be smaller than this threshold, defined by the user.

The general region growing algorithm is summarized as shown in Figure 3.1.

**Figure 3.1 Region growing algorithm.**

There are large number of region based segmentation approaches [23-25]. A color segmentation algorithm proposed by Deng and Manjunath uses a region growing process to segment the image based on multi-scale $J$ images [26]. The images which correspond to the measurements of local homogeneities at different scales are called as $J$ images. It indicates the potential boundary locations. The system has the ability to segment color-textured images and video sequences without supervision. First the colors inside the
images are quantized to several classes. This is helpful to distinguish various regions within an image. The pixels are then replaced by their corresponding color class label, which forms the class map of an image. The focus of this method is on the spatial segmentation. Here a principle for 'good' segmentation using class-map is proposed. J images are created by applying the criterion to local windows in the class-map. In the class map, high and low values correspond to the possible boundaries and the interiors of color-texture regions. A region growing method is then used to segment the image based on the multi-scale J-images. However, this method has certain limitations such as [26]:

1. The major problem is induced by varying shades due to the illumination. The problem is tricky to handle because, in many cases, not only the illuminate component but also the chromatic components of a pixel change their values due to the spatially varying illumination. This results in over segmentation into several regions.

2. In video segmentation using JSEG method, the main difficulty is that an error generated in one frame can affect to the succeeding frames.

### 3.3.2 Region Adjacency Graph

The adjacency relation among different regions in a scene can be represented by a region adjacency graph (RAG) [27]. Regions in the scene are represented by a set of nodes \( N = \{ N_1, N_2, \ldots, N_m \} \) where node \( N_i \) represent the region \( R_i \) in the scene and the properties of the region \( R_i \) is stored in the node data structure \( N_i \). The edge \( e_{ij} \) between \( N_i \) and \( N_j \) represents the adjacency between regions \( R_i \) and \( R_j \). Two regions \( R_i \) and \( R_j \) are said to be adjacent if a pixel in region \( R_i \) and a pixel in region \( R_j \) are adjacent to each other. The adjacency can be either 4-connected or 8-connected. The adjacency relation is reflexive and symmetric but not necessarily transitive. In Figure 3.2 (a), we show the adjacency graph of a scene with five distinct regions.

A graph-theoretic approach to the problem of color image segmentation was proposed in [28]. The method uses RGB and \( \text{L}^* \text{a}^* \text{b}^* \) color spaces for segmentation. The Euclidean distance metric is used to measure the color similarity between pixels. Regions are represented by vertices in the graph and the links between geometrically adjacent regions have the weights that are proportional to the color distance between regions to be merged. In next iteration, the weights of all links that are connected to a new region are
recomputed before the minimum weight link is selected. The links chosen in this way define a spanning tree on the original graph and the order in which links are chosen defines a hierarchy of image representations.

Figure 3.2 Region adjacency graphs (a) A scene with 6 distinct regions, (b) the adjacency graph of the scene.

3.3.3 Split and Merge

As opposed to region growing techniques of segmentation where a region is grown from a seed pixel, the split and merge technique subdivides an image initially into a set of arbitrary, disjointed regions and then merge and/or split the regions in an attempt to satisfy a homogeneity criterion between regions.

A split and merge algorithm that iteratively works towards satisfying this constraint was presented [5]. The author described the split and merge algorithm initially proposed [29]. The image is subdivided into smaller and smaller quadrant regions so that for each region a homogeneity criterion holds. That is, if for a region $R_i$, the homogeneity criterion does not hold, divide the region into four sub-quadrant regions and so on. This splitting technique may be represented in the form of a so-called quad-tree. The quad-tree data structures is the most common used data structure in split and merge algorithms because of its simplicity and computational efficiency. A splited artificial image and the corresponding quad-tree are as depicted in Figure 3.3 respectively. Note that the root of the tree corresponds to the entire image. Merging of adjacent sub-quadrant regions is allowed if they satisfy a homogeneity criterion. The procedure may be summarized as:
• Split into four disjointed quadrants any region where a homogeneity criterion does not hold.
• Merge any adjacent regions that satisfy a homogeneity criterion.
• Stop when no further merging or splitting is possible.

Most split and merge approaches to image segmentation follow this simple procedure with varying approaches coming from different color homogeneity criteria. A major drawback of quad-tree structured split and merge algorithms is their inability to adjust their tessellation to the underlying structure of image data because of the rigid rectilinear nature of the quad-tree structure [30].

![Quad-tree](image)

**Figure 3.3** Split and merge (a) Partitioned image (b) Corresponding quad-tree.

### 3.4 Edge-based techniques

Edge-based techniques focus on the discontinuity of a region within an image. Color edge detection techniques are being used today for image segmentation purposes. In color images, the information about edge is much richer than monochrome images. For example, an edge between two objects with same brightness but different hues can not be detected in monochrome image but can be found in color images. Once the edges within an image have been identified, the image can be segmented into different regions based upon these edges. Since edges are the local features, they are determined based on local information. A large variety of methods are available in the literature for edge finding [31-33].

Davis classified edge detection techniques into two categories: sequential and parallel [34]. In sequential technique the decision weather a point is an edge pixel or not is dependent on the result of detector at some previously examined pixels. On the other
hand, in parallel method the decision whether a point is an edge or not is made based on the point under consideration and some of its neighbouring points. As a result of this the operator can be applied to every point in the image simultaneously. The performance of a sequential edge detection method is dependent on the choice of an appropriate starting point and how the results of previous points influence the selection and result of the next point. There are different types of parallel differential operators such as Roberts’s gradient, Sobel gradient, Prewitt gradient, Laplacian and Canny operator. According to Canny, a good edge detector should have the following two properties [35]: (1) low probability of wrongly marking non-edge points and the low probability of failing to mark real edge points (i.e. good detection) (2) points marked as edges should be as close as possible to the center of true edges (i.e. good localization).

For color images, the notion of an edge is much more complex than in gray-scale images. In color images, intensity, hue and saturation of color all plays an important part in determining the object boundaries [36]. A physical boundary produces an edge which needs to be captured using a measure that combines the different color characteristics. The concept of color similarity now becomes important since pixel intensities alone cannot be used to determine the existence of an edge. For color images, a number of approaches have been proposed from processing individual planes to true vector-based approaches [32,37]. The computational load of computing edges on individual planes can be much smaller than that of computing edges on the color vector. However, this seems to be a trade-off between speed and algorithm performance. The vector-based approaches exploit the correlation between color planes much more effectively than the computation on single planes. This is why most researchers have concentrated on vector-based approaches. However, a drawback with edge-based techniques is their sensitivity to noise; also in most cases the edge detection strategies ignores the higher order organization which may meaningfully present in the image [38].

3.5 Fuzzy techniques

The segmentation approaches discussed so far takes the crisp decisions about regions. Nevertheless, the regions in an image are not always crisply defined and uncertainty can arise within each level of image analysis and pattern recognition [39]. It may occur at low level in the raw sensor output, and extend all the way through intermediate and higher
levels. A recognition or computer vision system must have sufficient flexibility for processing of uncertainty in any of these levels so that the system could retain as much as information possible at each level. In this way, the final output of the system may not be biased too much by lower level decisions, unlike the classical approaches. As image segmentation is the first essential step of a recognition or vision system, it particularly should have such a provision for representing and manipulating the uncertainties.

Fuzzy set theory provides a mechanism to represent and manipulate uncertainty and ambiguity [40]. Fuzzy operators, properties, mathematics, and inference rules (IF-THEN rules) have found considerable applications in image segmentation. In fuzzy subsets, each pixel in an image has a degree to which it belongs to a region or a boundary, characterized by a membership value. By doing so, we can avoid making a crisp decision earlier and keeps the information through the higher processing levels as much as possible. Recently, there has been an increasing use of fuzzy logic theory for color image segmentation [19, 41, 42].

FCM is a well-known algorithm for clustering. Lim and Lee introduced a segmentation algorithm for color images based on histogram thresholding and FCM algorithm [43]. It uses a scale space filter to analyze the histogram of three-color component. The segmentation is performed in color space proposed by Ohta. The image is first segmented coarsely using multithresholding. The coarse segmentation is then polished using FCM clustering technique. Hall used a FCM clustering technique to segment MR images where each pixel is a 3-D vector consisting of different features yielded by the MRI system [44]. Tolias and Panas proposed an algorithm that combines the result of performing FCM algorithm on a set of different resolution of the original image [45]. Using FCM algorithm, Bezdek proposed a segmentation algorithm that uses a region growing concepts and the pyramidal data structure (PDS) for the hierarchical analysis of an aerial image [46].

A novel approach for color image segmentation is proposed by Cheng and Jiang [47]. The system uses homogram based approach (HOB) to detect homogeneous regions within color images. The homogram considers both the local as well as global information of a pixel. The threshold values in each plane are found out using fuzzy homogeneity approach. The method uses fuzzy entropy criterion to perform homogram
analysis to find all major homogeneous regions. Region merging process is carried out based on color similarity among these regions to avoid over segmentation. Segmentation results for the corresponding color components are then combined.

However, clustering technique to image segmentation suffers from the problems related to:

- Adjacent clusters frequently overlap in color space causing incorrect pixel classification.
- Clustering is more difficult when the number of clusters is unknown, as is typical for segmentation algorithms.

### 3.6 Neural network approaches

Neural networks are formed by several elements that are connected by links with variable weights. ANN is widely applied for pattern recognition. It is a physical cellular network that is able to acquire, store, and utilize experiential knowledge that has been related to network's capabilities and performance [48]. Their processing capability and nonlinear characteristics are used for classification and clustering. ANN explore many competing hypotheses simultaneously through parallel nets instead of performing a program of instructions sequentially, hence it can be feasible for parallel processing. The complete network, therefore, represents a very complex set of interdependencies which may incorporate any degree of nonlinearity, allowing very general function to be modeled. Training time is usually very long, but after training, the classification using ANN is rapid.

Self-organization of Kohonen Feature Map (SOFM) network is a powerful tool for data clustering [49]. It projects the input space on prototypes of low-dimensional regular grids that can be effectively utilized to visualize and explore properties of data. Lo and Pei proposed a technique for color image segmentation [10]. SOFM is used for quantization of the input color image to reduce computational time, and obtained an indexed image. A local histogram is calculated using a moving window and index-count vectors are obtained. The index-count vectors are used as the training data for SOFM. Finally, each cluster is mapped from index-count space to the original image.

Li and Li proposed an adaptive approach for color image segmentation [50]. The method uses neural network based approach to find automatic features of an image. The
multiple color features can be analyzed using a self organizing feature map (SOFM). A useful feature sequence (feature vector) is determined. The encoded feature vector can be used in the final segmentation. The method uses FCM algorithm for clustering. One of the advantages of this method is that, with SOFM, a feature vector suitable for segmenting the input image can be extracted automatically. Consequently, this technique is an adaptive approach for segmenting different types of color images.

There are also some other neural networks such as Oscillatory cellular neural network (OCNN), Generalized adaptive neural filter (GANF), Hopfield neural networks (HNN), which can be used to segment color images [51]. An oscillatory cellular neural network (OCNN) is employed to segment color images [52]. Its architecture consists of an array of simple neural oscillators with inter-connections limited to the nearest neighbourhood. The advantage of OCNN is that it solves a bottleneck created by the immense number of interconnections between a global separator and the oscillators. Connectedness between neighbouring color pixels is defined as color connectedness matrix (CCM) to group the correlated segments. Simulation results demonstrate the validity and performance of OCNN. GANF is one of the artificial neural networks, which is used for noise removal [53]. It consists of neural operators based on stack filter that uses the binary decompositions of gray value data. Sammouda proposed an unsupervised algorithm, which uses HNN to segment color images of liver tissues [54]. The method can automatically extract the nuclei region and the cytoplasm region, which are useful for diagnosis.

3.7 Hybrid techniques

A number of hybrid color image segmentation techniques were introduced recently [38, 55]. This technique combines the benefits of various techniques mentioned in past sections and makes the disadvantages of others. Tseng and Chang proposed a segmentation scheme that first splits the color image into chromatic and achromatic regions and then employs a histogram thresholding technique to two different regions, separately [55]. The scheme can be summarized in following two steps.

- Convert RGB color values through XYZ and $L^*u^*v^*$ space to HSI color values.
- Define effective ranges of hue and saturation in the HSI space and determine chromatic and achromatic regions within an image.
• Use hue, saturation, and/or intensity one-dimensional histogram thresholding to further segment the image.

• Detect and recover over-segmentation regions using region merging technique.

3.8 Remarks

Color image segmentation is crucial for multimedia applications. Multimedia databases utilize segmentation for the storage and indexing of images and video. Image segmentation is used for object tracking in the new MPG-7 video compression standard. It is usually the first task of any image analysis process and thus subsequent tasks depend heavily on the quality of segmentation. A number of color image segmentation techniques have been surveyed in this chapter. They are summarized in Table 3.1.

Most of the gray level image segmentation techniques could be extended to color image, such as histogram thresholding, clustering, region growing, edge detection, fuzzy based approaches, neural network based approaches and hybrid approaches. They can be directly applied to each component of a color space; the results can be combined in some way to obtain final segmentation result. However, one problem is how to employ the color information as a whole for each pixel. When a color is projected onto three components, color information is so scattered that the color image becomes simply a multispectral image and the color information that human can perceive is lost. Another problem is how to choose the color representation for segmentation, since each color representation has its advantages and disadvantages.

Fuzzy set theory has attracted more and more attention in image processing area. It provides a suitable tool which represents uncertainties arising in image segmentation and can model the cognitive activity of human beings. Fuzzy operators, properties, mathematics, and inference rules (IF THEN rules) have found more and more applications in image segmentation. The more important advantage of fuzzy methodology lies in fuzzy membership function that provides a natural means to model uncertainty within an image. Subsequently, fuzzy segmentation results can be utilized in feature extraction and object recognition phases of image processing and computer vision. Fuzzy approach provides a promising means for color image segmentation. In next chapter, we proposed a neuro-fuzzy approach for color image segmentation.
the experimental results, performance of the proposed technique was found satisfactory. The system can be used as a primary tool to segment unknown color images.

### Table 3.1 Image segmentation techniques

<table>
<thead>
<tr>
<th>Segmentation technique</th>
<th>Method description</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Histogram thresholding</strong></td>
<td>Regions are determined by thresholding peaks in the histogram.</td>
<td>It does not need <em>a priori</em> information of an image.</td>
<td>Does not work well for an image without obvious peaks.</td>
</tr>
<tr>
<td></td>
<td>Simple to implement.</td>
<td>For a wide class of images satisfying the requirement, this method works well with low computation complexity.</td>
<td>Does not consider the spatial details, so can't guarantee that the segmented regions are contiguous.</td>
</tr>
<tr>
<td></td>
<td>No spatial consideration.</td>
<td>Work best when the region homogeneity criterion is easy to define.</td>
<td>Region growing has inherent dependence on the selection of seed region and the order in which pixels and regions are examined.</td>
</tr>
<tr>
<td><strong>Region based approaches</strong></td>
<td>Group pixels into homogeneous regions.</td>
<td>They are also more noise immune than edge detection approach.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>It includes region growing, region splitting, region merging or their combination.</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Edge detection approaches</strong></td>
<td>Based on the detection of discontinuity.</td>
<td>Edge detecting technique is the way in which human perceives objects and works well for images having good contrast between regions.</td>
<td>Does not work well with images in which the edges are ill-defined or there are too many edges.</td>
</tr>
<tr>
<td></td>
<td>Normally tries to locate points with more or less abrupt changes in gray level.</td>
<td></td>
<td>It is not a trivial job to produce a closed curve or boundary.</td>
</tr>
<tr>
<td></td>
<td>Usually classified into two categories: sequential and parallel.</td>
<td></td>
<td>Less immune to noise than other techniques, e.g., thresholding and clustering.</td>
</tr>
<tr>
<td>Clustering</td>
<td>Assumes that each region within an image forms a separate cluster in the feature space. Can be generally broken into two steps: (1) categorize the points in the feature space into clusters; (2) map the clusters back to the spatial domain to form separate regions.</td>
<td>Straightforward for classification. Easy for implementation.</td>
<td>Determination of number of clusters (known as cluster validity). Features are often image dependent and how to select features so as to obtain suitable segmentation results remains unclear. Does not utilize the spatial information. Are by nature sequential and quite expensive both in computational time and memory.</td>
</tr>
<tr>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td><strong>Fuzzy approaches</strong></td>
<td>Apply fuzzy operators, properties, mathematics, and inference rules (IF-THEN rules). Provide a way to handle the uncertainty inherent in a variety of problems due to ambiguity rather than randomness.</td>
<td>Fuzzy membership function can be used to represent the degree of some properties or linguistic phrase, and fuzzy IF-THEN rules can be used to perform approximate inference.</td>
<td>Determination of fuzzy membership is not a trivial job. Computations involved in fuzzy approaches could be intensive.</td>
</tr>
<tr>
<td><strong>Neural network approaches</strong></td>
<td>Using neural networks to perform classification or clustering.</td>
<td>No need to write complicated programs. Can fully utilize the parallel nature of neural networks.</td>
<td>Training time is long. Initialization may affect the results. Overtraining should be avoided.</td>
</tr>
<tr>
<td><strong>Hybrid techniques</strong></td>
<td>Most common techniques of color image segmentation today.</td>
<td>Combine the benefits of various methods mentioned in past sections and makes the disadvantages of others.</td>
<td></td>
</tr>
</tbody>
</table>
References


