A Survey on Multi-Level Thresholding for Color Image Segmentation

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ABSTRACT - Color image segmentation is used to retrieve the intended information for subsequent image analysis. Based on the intensity levels, the image pixels are arranged, and the segmentation is carried out for predicting the image information. The objective functions are optimized by the best segmentation scheme for suitable threshold value determination. Literature presents various techniques such as thresholding, edge-based, region-based, neural network-based segmentation etc. The main challenge is to select the precise threshold for complex color images, improving the accuracy. This paper deals about different algorithms for color image segmentation using different objective functions.

Key words : color image segmentation, multilevel thresholding

I. INTRODUCTION

Image processing finds wide range of application in pattern recognition, robotic systems, medical imaging and automatic target recognition etc [1]. Image segmentation partitions the image into various regions to infer about the object of interest. Each region in the image is homogeneous and the segmentation process is carried out based on the intensity, color and texture.

Recently, color image segmentation drifted the attention due to the reliable segmented output of color images than gray-scale images. The high computational power of computers enables to process the color images effectively. Color image segmentation separates the spatial attributes same as the task accomplished by our visual system. Literature introduces many segmentation techniques as the image segmentation is a psychophysical perception [2].

II. CLASSIFICATION OF SEGMENTATION TECHNIQUES

Segmentation of color images employing the widely used RGB (red, green and blue) color spaces are extended through histogram thresholding, edge detection, region-based methods, fuzzy techniques, neural networks etc [3]. Generally, color image segmentation algorithms work on various metrics and color spaces. Every color in tri-dimensional co-ordinated system is represented by a distinctive point. The red, green and blue wavelengths are tuned by the photo receptors of retina known as cones.

The commonly used RGB color space for image displaying, storage and image acquisition is used in televisions, CMY (cyan, magenta, yellow) color model for printers. RGB space is the basic for computers and in digital cameras. The cube shaped representation of RGB component ranges from 0 to 255. The cone shaped HSV (hue, saturation and values) ranges from [0,2π], saturation with [0,1]and with intensity [0,255].

The CIE - Commission Internationale de L'Eclairage developed various color spaces such as YUV, YCbCr, L*,u*v*and L*,a*,b*[L* represents the intensity ranging from [0,100], the intensity a*, b* from[-127,128] and the u*,v* from [-175,175]. In digital television YUV, YCbCr is most commonly used and the Y is the luminance and (UV, CbCr are the chrominance components).

1. Edge detection technique

This technique is suitable for gray scale images. This technique works better for the images perceiving good contrast but less immune to noise. It detects the brightness discontinuity in an image by representing the boundary between two objects with different intensities. This method smoothens the image with gaussian low pass filter and supress the noise. Then, the smoothed image is computed for local gradient at each point and the resulted ridge pixels are thresholded.

2. Thresholding based technique

Image segmentation through thresholding provide useful information to be analysed using image histogram. This method finds the peak, valleys in intensity histogram. The histogram thresholding identifies the object of interest pixel by pixel. The main advantage of this method is it does not require any prior information about the image. This technique works on wide class of images. The p-tile method predicts the brighter objects with respect to background and the mean value technique calculates the mean value of pixels as threshold. Thresholding technique is generally classified into bilevel and multilevel thresholding. Bilevel thresholding (BLT) divides the image into foreground and background using single threshold value, whereas multilevel thresholding provides the various classes of image information. In general, the thresholding methods employ parametric and non-parametric approaches. The computed thresholds of

2.1 Maximum entropy (Kapur objective function)

In general, the desired content of the image is predicted using probability distribution of gray histogram [4].

The maximization objective function of Kapur's bi-level thresholding is given as:

The image with L intensity level with N number of pixels for bilevel thresholding can be given as:

$$x(t) = B_0^C + B_1^C$$

where,
$$B_0^C = -\sum_{i=0}^{t-1} \frac{P_i^C}{k_0^C} ln \frac{P_i^C}{k_0^C}$$

$$k_0^C = \sum_{i=0}^{t-1} P_i^C$$

$$B_1^C = -\sum_{i=0}^{L-1} \frac{P_i^C}{k_1^C} ln \frac{P_i^C}{k_1^C}$$

$$k_1^C = \sum_{i=0}^{G-1} P_i^C$$

$$C = \begin{cases} 1,2,3, & \text{for RGB image} \\ 1, & \text{for gray scale image} \end{cases}$$

where $P_i^C = \frac{h_i^C}{\sum_{i=0}^{L-1} h^C(i)}$

The optimal threshold value

$$t^{*C}(t) = \arg\max(B_0^C + B_1^C)$$

Kapur's multilevel thresholding extension is given as:

$$x(t) = \sum_{i=0}^{y-1} B_i^C$$

The image is divided into *f* classes by *f-1* thresholding values. Extension of Kapur's entropy for multielevel thresholding image segmentation is presented as:

$$B_0^C = -\sum_{i=0}^{t_1-1} \frac{P_i^C}{k_0^C} ln \frac{P_i^C}{k_0^C}$$

$$k_0^C = \sum_{i=0}^{t_1-1} P_i^C$$

$$B_1^C = -\sum_{i=t_1}^{t_2-1} \frac{P_i^C}{k_1^C} ln \frac{P_i^C}{k_1^C}$$

$$k_1^C = \sum_{i=t_1}^{t_2-1} P_i^C$$

multilevel thresholding (MLT) using various objective functions using non-parametric approaches such as Otsu, Kapur, minimum cross entropy, Reny, Tsallis reveal the information to be analysed from an image.

$$B_j^C = -\sum_{i=t_j}^{t_{j+1}-1} \frac{P_i^C}{k_j^C} ln \frac{P_i^C}{k_j^C}$$

$$k_j^C = \sum_{i=t_j}^{t_{j+1}-1} P_i^C$$

$$B_{f-1}^C = -\sum_{t_{f-1}}^{G-1} \frac{P_i^C}{k_{f-1}^C} ln \frac{P_i^C}{k_{f-1}^C}$$

$$k_{f-1}^C = \sum_{i=t_{f-1}}^{G-1} P_i^C$$

The optimal multilevel thresholding in multidimensional optimization problem is used to find *f-1* optimal threshold values $t_1, t_2, \ldots, t_{f-1}$.

Thus, the maximized objective function of Kapur's entropy is given as:

$$(t_1^{*C}, t_2^{*C}, \ldots\ t_{f-1}^{*C}) = \arg\max(\sum_{i=0}^{y-1} B_i^C)$$

2.2 Between-class variance method (Otsu method)

The object of interest is evaluated by maximising between-class variance through Ostu's non-parametric objective function [4].

The image with '*G*' gray levels with *N* pixels and the number of pixels with gray level *i* is determined by z_i. The probability event of gray level *i* is represented as:

$$Pb_i^C = \frac{z_i^C}{N},\ Pb_i^C \geq 0$$

$$\sum_{i=0}^{G-1} Pb_i^C = 1$$

Bilevel thresholding for Otsu method is given as:

$$x^C(t) = \sigma_0^C + \sigma_1^C$$

$$\sigma_0^C = k_0^C\,(\mu_0^C - \mu_T^C)^2$$

$$\sigma_1^C = k_1^C\,(\mu_1^C - \mu_T^C)^2$$

where $\mu_T^C = \sum_{i=0}^{G-1} iP_i^C$

Mean level of bi-level classes as:

$$\mu_0^C = \sum_{i=0}^{G-1} \frac{iPb_i^C}{k_0^C}$$

$$\mu_1^C = \sum_{i=1}^{G-1} \frac{iP_i^C}{k_1^C}$$

The cumulative probabilities of the classes are as follows:

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$$k_0^C = \sum_{i=0}^{m-1} Pb_i^C$$

$$k_1^C = \sum_{i=m}^{G-1} Pb_i^C$$

Thus, the optimal threshold $t^{*C}$of Otsu by maximizing between class variance is obtained as:

$$t^{*C} = arg\ max(\sigma_0^C + \sigma_1^C)$$

The image is classified into *f* classes and with *f-1* where $\sigma_B^C = \sigma_0^C + \sigma_1^C + \cdots + \sigma_{y-1}^C$

The sigma terms are:

$$\sigma_0^C = k_0^C\,(\mu_0^C - \mu_T^C)^2,$$

$$\sigma_1^C = k_1^C\,(\mu_1^C - \mu_T^C)^2, .., \sigma_{f-1}^C = k_{f-1}^C\,(\mu_{f-1}^C - \mu_T^C)^2$$

The mean levels of *f* classes are given as:

$$\mu_0^C = \sum_{i=0}^{t_1-1} \frac{iPb_i^C}{k_0^C}$$

$$\mu_1^C = \sum_{i=m_1}^{t_2-1} \frac{iPb_i^C}{k_1^C} \ldots$$

$$\mu_{f-1}^C = \sum_{i=t_{f-1}}^{L-1} \frac{iPb_i^C}{k_{f-1}^C}$$

The value of '*C*' for gray scale image is assigned with '*C*' with *1* and *C = 1,2,3* for *RGB* image multilevel thresholdingrespectively.

2.3 Minimum Cross Entropy (MCE) objective function

Minimum Cross entropy (MCE) maximises the total entropy values by calculating the deviation between standard and actual distribution. The MCE was proposed by Kullback to maximise the entropy values [5].

Bi-level thresholding for MCE is given as:

$$\min\{E^C(\mathrm{t})\} = E_0^C + E_1^C$$

$$E_0^C = -\sum_{i=0}^{t-1} ig^C(i)\,log\left(\frac{\sum_{i=0}^{t-1} ig^C(i)}{\sum_{i=0}^{t-1} g(i)}\right)$$

$$E_1^C = -\sum_{i=t}^{L} ig^C(i)\,log\left(\frac{\sum_{i=t}^{Y} ig^C(i)}{\sum_{i=t}^{Y} g(i)}\right)$$

Extension of multilevel thresholding for minimum cross entropy '*n*' dimensional optimization, the objective function is given as:

$$\min\{E^C(t_0^C + t_1^C + t_2^C + \cdots + t_n^C) = E_0^C + E_1^C + E_2^C + \cdots + E_n^C$$

where,

thresholding values. The Otsu between-class variance for multilevel thresholding is given as:

$$x^C(t) = \sum_{i=0}^{y-1} \sigma_i^C$$

By maximizing σ_B^C, the optimal thresholding values of $(t_1^{*C}, t_2^{*C}, \ldots\, t_{y-1}^{*C})$are computed as:

$$(t_1^{*C}, t_2^{*C}, \ldots\, t_{f-1}^{*C}) = \underset{0\le t_1^{*comp} \le, \ldots\, t_{y-1}^{*comp} \le L-1}{arg\quad max}\{\sigma_B^C(t_1^{*C}, t_2^{*C}, \ldots\, t_{f-1}^{*C})\}$$

$$E_0^C = -\sum_{i=0}^{t_1-1} ig^C(i)\,log\left(\frac{\sum_{i=0}^{m_1-1} ig^C(i)}{\sum_{i=0}^{m_1-1} g^C(i)}\right)$$

$$E_1^C = -\sum_{i=t_1}^{t_2-1} ig^C(i)\,log\left(\frac{\sum_{i=m_1}^{m_2-1} ig^C(i)}{\sum_{i=m_1}^{m_2-1} g^C(i)}\right)$$

$$E_2^C = -\sum_{i=t_2}^{t_3-1} ig^C(i)\,log\left(\frac{\sum_{j=m_2}^{m_3-1} ig^C(i)}{\sum_{j=m_2}^{m_3-1} g^C(i)}\right) \ldots$$

and

$$E_n^C = -\sum_{i=n}^{L} ig^C(i)\,log\left(\frac{\sum_{i=n}^{L} ig^C(i)}{\sum_{i=n}^{Y} g^C(i)}\right)$$

2.4 Region based technique

This technique partitions the regions with respect to the desired content of the image. This method is immune to noise and works better when the homogeneity criteria for the region is well define and this technique is classified into region growing, region splitting and merging. Based on spatial coherence, this method divides and merge the existing regions of an image and the regions are grown from the seed points.

2.4 Feature clustering technique

The most effective straight forward tool for implementation and classification is Fuzzy C-means and K-means algorithm. The fuzzy membership functions and fuzzy if-then rules are used for accurate image segmentation. The pixel can be a part of more than a cluster with a membership level associated. This method places the centre of cluster arbitrarily for the desired number of clusters and the cluster centres are recomputed by averaging the pixel in clusters.

2.5 Neural network-based technique

High degree of parallelism with fast computation is achieved by imitating the functions of human brain with collection of neural units known as artificial neuron. Parallel nature of neural network overcome the complexity of complex programming but requires a long training time.

Generally, segmentation methods are used to improve

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the speed and accuracy for image interpretation.

Various image segmentation algorithms by Siang Tan and Mat Isa [6] used histogram thresholding and improved the compactness of the clusters using Fuzzy C-means hybrid approach. This method provided more homogenous segmented regions. Bakhshali and Shamsi [7] introduced a new color space (IHLS) resulted as the combination of (HLS, HIS and HSV) for facial image segmentation based on bacterial foraging optimization. Sarkar et al. [8] proposed a multilevel thresholding using minimum cross entropy. Computational time and robustness ae improved by differential evolution (DE) algorithm and the statistical region merging (SRM) is applied to obtain distinguishable regions. Zhang et al. [9] Al used fast segmentation method to identify foreign fibres in cotton. This technique used edge detection method to produce the best segmentation output through best thresholding value of gradient map. Sağ and Çunkaş [10] presented an improved artificial bee colony algorithm for multi objective optimization (IBMO). Feature extraction such as color, texture is measured by seeded region growing (SRG) with IBMO. Sathya and Kayalvizhi [11] introduced a modified bacterial foraging algorithm using Otsu-Kapur maximisation objective functions for precise global search of optimal thresholds improving the computational speed. Bhandari et al. [12] proposed cuckoo search algorithm with wind driven optimisation to find the perfect threshold values for image segmentation using Kapur's entropy fitness function.

III. CONCLUSION

The cardinal motivation to analyse, classify and to extract the information in an image is easily performed through image segmentation. In this paper, color spaces such as RGB, HSV, L*a*b*, L*u*v*, YUV and YCbCr and various color image segmentation techniques are discussed. RGB color space is widely used for color displaying devices and (HSV, L*a*b*, L*u*v*, YUV and YCbCr) decouple the intensity from chromaticity improving the color recognition as human identify the color by chromaticity. This paper presented the survey on various segmentation techniques with various objective functions.

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