Edge based technique to estimate Number of Clusters in k-means Color Image Segmentation

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***Abstract*—K-Means algorithm is an unsupervised clustering algorithm that classifies the input data points into multiple classes based on their inherent distance from each other. Success of k-means color image segmentation depends on parameter k. If numbers of clusters are estimated correctly, k-means image segmentation can provide good results. This paper proposes a novel method based on edge detection to estimate number of clusters automatically. Edges are detected in terms of phase congruency. Short edges reflect the local character in image while long edges are more important to estimate number of clusters. The short edges are eliminated. Edge line clustering is used to group long edges based on color similarity. For grouping color similar edges average color of each edge is calculated. Euclidean distance on average color of each pair of edges is calculated. Long edges assigned same label if Euclidean distance on average color is less. We have estimated the number of clusters in image using edge line clustering. The number of edges left after edge line clustering is thought as number of clusters in image. This value is used as value of k for k-means image segmentation.**

Keywords-Phase congruency, K-means, Edge line clustering, Euclidean Distance

I. INTRODUCTION

Color images are more complex than gray scale images as instead of a single gray scale value for a pixel, each pixel is usually represented by three color values, such as red, green and blue. Clustering based methods are ideal to use for segmentation of color images as the methods used for gray scale images can be easily extended to higher dimensions. However, the increased dimensionality leads to a more computationally expensive process. Clustering methods can be divided into two basic types; hierarchical and partitional clustering. Hierarchical clustering proceeds successively by either merging smaller clusters into larger ones or by splitting larger clusters into smaller ones. Many hierarchical methods have been proposed of which some are agglomerative and some are divisive. Partitional techniques form clusters by optimizing a clustering criterion, where the classes are mutually exclusive thus forming a partition of the data [2].

Statistical clustering is the most common form of clustering, which involves assigning each occurrence of a particular color to one particular cluster regardless of whether each pixel having the color are located near each other spatially in the image, in which case these pixels would not form a valid segment from the visual point of view [2].

In his thesis, Rose H. Turi [2] has given brief mention of clustering techniques. Many clustering based segmentation methods have been proposed and the most popular of these are the K-means, fuzzy K-means. Most of the clustering methods have a common failing, which is that the number of clusters usually must be supplied, or if splitting or merging is incorporated, the stopping criterion is based on too many parameters. A good clustering based segmentation method should automatically determine the number of clusters present in the image and it should, and it should not rely on as few parameters as possible, preferably none, so that final result is not biased by the choice of parameter values [2].

This paper proposes a robust method based on edge detection to determine number of clusters automatically. Long edges estimate rough distribution of objects in image[1]. For edge detection illumination invariant feature detector phase congruency is utilized. The use of phase congruency for marking features has significant advantages over gradient-based methods [3]. Phase congruency is a dimensionless quantity that is invariant to changes in image brightness or contrast; hence, it provides an absolute measure of the significance of feature points, thus allowing the use of universal threshold values that can be applied over wide classes of images. Long edge lines are grouped to different classes with a high level of homogeneity to estimate the number of clusters in image, while short ones are removed. For grouping color similar, edge descriptor for each edge is determined which contains average color of edge, centroid and number of pixels in edge. If number of pixels for edge fall below threshold, edge is removed. Edges are assigned same label if Euclidean distance on average color of edges is less than threshold. Edges left after edge line clustering is thought as number of clusters in image. This value is used as value of k in k-means color image segmentation

II. K-MEANS CLUSTERTING ALGORITHM

The k-means algorithm is one of the simplest clustering techniques for which the objective is to find the partition of the data which minimizes the squared error or the sum of squared distances between all points and their respective cluster centers [2]. K-means uses an iterative algorithm that minimizes the sum of distances from each object to its cluster centroid, over all clusters. This procedure consists of following steps as follows.

1) Randomly choose k data points from the whole dataset as initial clusters. These data points represent initial cluster centroids.

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2) Calculate Euclidean distance of each data point from each cluster centre and assign the data points to its nearest cluster centre

3) Calculate new cluster centre so that squared error distance of each cluster should be minimum.

4) Repeat step 2 and 3 until clustering centers do not change.

5) Stop the process.

In the above algorithm, the cluster centers are only updated once all points have been allocated to their closed cluster centre. The advantage of K-means are that it is a very simple method, and it is based on intuition about the nature of a cluster, which is that the within cluster error should be as small as possible. The disadvantage of this method is that the number of clusters must be supplied as a parameter, leading to the user having to decide what the best number of clusters for the image is [2]. Success of k-means algorithm depends on the parameter k, number of clusters in image. This paper proposes unsupervised method to determine number of clusters automatically.

III. Edge Detection Via Phase Congruency

An edge may be regarded as a boundary between two dissimilar regions in an image, which may be different surfaces of the object, or perhaps a boundary between light and shadow falling on a single surface [10]. Most edge detection methods work on the assumption that an edge occurs where there is a discontinuity in the intensity function or a very steep intensity gradient in the image. Gradient-based edge-detection methods such as those developed by Sobel , Marr and Hildreth, Canny, and others are sensitive to variations in image illumination, blurring, and magnification [3]. Image features such as step edges, lines, and Mach bands all give rise to points where the Fourier components of the image are maximally in phase [6]. The use of phase congruency for marking features has significant advantages over gradient-based methods. Phase congruency is a dimensionless quantity that is invariant to changes in image brightness or contrast. This section presents a new measure of phase congruency proposed by Peter Kovesi [3].

Peter Kovesi [3] proposed a method to calculate the phase congruency via logarithmic Gabor wavelets. Log Gabor wavelets are used because they can cover large frequency space while still maintaining a zero DC component in the even symmetric filter. Filters are constructed in the frequency domain using a polar co-ordinate system. The filter has two components radial component and angular component. Two components are multiplied to construct the overall filter. To calculate phase congruency image convolution is done with a set of log Gabor wavelets at different orientations and at different scales. 1-D log Gaussians in the radial direction has a transfer function of the form

$$g(w) = e^{\frac{-(\log(w/w\ ))^2}{2(\log(k/w_0))^2}} \qquad (1)$$

Where w_0 is the centre frequency of filter. To obtain constant-shape ratio filters the term k/w_0 must also be held constant for varying w_0.

The Gaussian cross-section in the angular direction is defined as

$$G(\theta) = \frac{(\theta - \theta_o)^2}{2\sigma_\theta{}^2} \qquad (2)$$

Where θ_o is the orientation angle of the filter, and σ_o is the standard deviation of the Gaussian function in the angular direction. Then at each location in the image, calculate energy *E(x)* in each orientation, subtract the estimated noise effect T_o to eliminate spurious responses to noise. Phase congruency is significant only if it occurs over a wide range of frequencies. Apply the weighting for frequency spread $W_o(x)$, and form the sum of energies over all orientations. This sum of energies is then normalized by dividing by the sum of amplitudes over all orientations and scales of the amplitudes of the individual wavelet responses at that location in the image.

This produces the following equation for 2-D phase congruency.

$$E_{no} = A_{no} \nabla \phi_{no}(x) \qquad (3)$$

$$PC(x) = \frac{\sum_o \sum_n \lfloor E_{no}(x) - T \rfloor}{\sum_o \sum_n A_{no}(x) + \varepsilon} \qquad (4)$$

Where $A_{no}(x)$ is the amplitude of the filter pair at position x. o and n denote the index over orientation and scale respectively.

The phase deviation function is defined as,

$$\Delta\phi(x) = \cos(\phi_n(x) - \bar{\phi}(x)) - [\sin \phi_n(x) - \bar{\phi}(x))] \qquad (5)$$

The Compensation of noise T is defined as

$$T = \mu_R + k\sigma_R \qquad (6)$$

Where μ_R and S_R are the mean and variance of Rayleigh distribution. The phase congruency weighting function is defined as

$$W(x) = \frac{1}{1 + e^{g(c - s(x))}} \qquad (7)$$

$$s(x) = \frac{1}{N}\left(\frac{\sum_n A_n(x)}{\varepsilon + A_{\max}(x)}\right) \qquad (8)$$

Where N is the number of scales, $A_{max}(x)$ is the amplitude of the filter pair having maximum response at position x, ε is a small constant to avoid division by zero, c is the cutoff value of filter response spread below which phase congruency values become penalized.

The edge maps are obtained by performing nonmaximal suppression and hysteresis thresholding on the raw phase congruency images. In our experiment, we used two-octave bandwidth filters over four scales and six orientations to obtain local frequency information. The scaling between successive scales was 2. The ratio between the angular spacing of the filters and angular standard deviation of the Gaussians was 1.2.

A. *Non-maximal Suppression*

Each pixel in turn forms the centre of a nine pixel neighborhood. By interpolation of the surrounding discrete grid values, the gradient magnitudes are calculated at the neighborhood boundary in both perpendicular directions perpendicular to centre pixel. If the pixel under consideration is not greater than these two values, it is suppressed [10].

B. *Hystersis Thresholding*

An upper and lower edge value limits are set. If a value lies above the upper limit it is immediately accepted. If the value lies below the low threshold it is immediately rejected. Points which lie between the two limits are accepted if they are connected to pixels which exhibit strong response [10]. We used 0.4 and 0.6 values for lower and upper threshold respectively.

IV. ESTIMATING NUMBER OF CLUSTERS

Edge information is used to estimate number of clusters. Although idea of using edge information into image segmentation was used by Xu Jie and Shi Peng fei [1] to estimate rough distribution of objects in image and to determine initial seeds for region growing algorithm, this paper uses it to determine number of clusters for k-means algorithm. Short edges are considered as trivial details which normally caused due to texture of objects while long edges are important to estimate number of clusters in image. Long edges are assigned same label if edges are similar in color. Although HSV color space and Euclidean distance are used in the mentioned scheme, other color spaces and distance metrics can also be used. Determining number of clusters has following steps

1) Edges are detected in terms of phase congruency. Edge map is obtained by performing non maximal suppression and hysteresis thresholding

2) The 8-neighbor edge pixels are connected into a line. Determine edge descriptor for each edge

$$ED_i = \{h, s, v, percent, C_x, C_y\}$$

Where h, s, v is the average color components of edge. Percent is the ratio of number of pixels on line i to the total number of pixels in image. (Cx, Cy) is the centroid, defined as an algebraic average of pixels.

3) If number of pixels in edge is less than threshold then edge is removed.

4) Euclidean distance on average color of each pair of edges is calculated. Edges assigned same label if Euclidean distance on average color fall below threshold. Process is repeated until the Euclidean distance is greater than threshold.

5) The number of edges left after combining color similar edges is thought as number of clusters in image. This value is used as value of k for k-means algorithm.

V. EXPERIMENTAL RESULTS

MATLAB image processing tools were used to implement system. We follow here embedded integration strategy for image segmentation. Edge information is used to estimate number of clusters in image. We use illumination invariant feature detector phase congruency to determine edges. Edge maps were obtained by performing non-maximal suppression and hysteresis thresholding. Edge line clustering technique is utilized to determine number of clusters in image. Number of edges left after edge line clustering is thought as number of clusters in image. Then K-means image segmentation technique is utilized to obtain final results. Results were obtained for both synthetic and natural images.

TABLE I. RESULT ANALYSIS

Image	Number of clusters in the reference Image	Actual Number of Clusters Estimated
Bird	2	1
Hand	3	2
House	6	6
Airplane	2	2
Pears	7	8
Pigeon	3	2
Nature Scene	6	7
Pillstec	7	7
Saturn	6	5

VI. CONCLUSION

Success of K-means image segmentation depends on parameter K. If number of clusters is estimated correctly, it can provide very good results. We have proposed unsupervised image segmentation algorithm which integrates edges detection and K-means segmentation. Edge information is used to estimate number of clusters in image. To measure accuracy of proposed method we have compared, estimated number of clusters with number of clusters in reference image Estimated number of clusters are found mostly equal to number of clusters in image except little deviation for some natural images.

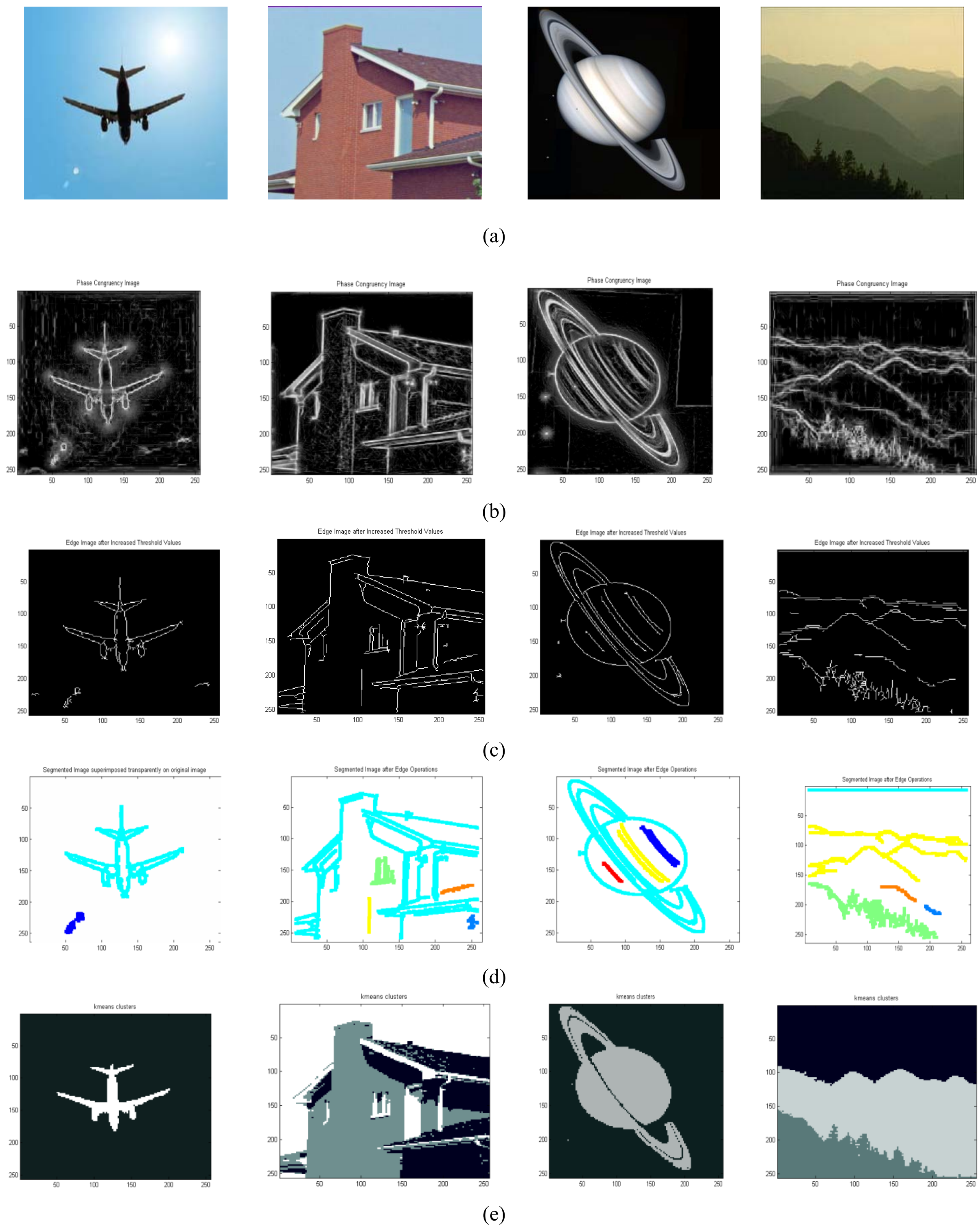

Figure 1. (a) Original Images (b) Phase Congruency Image (c)Edge image (d)Edge maps after combining color similar Edges (e) Final K-means Segmentation Results

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