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Object Segmentation in Color Images Using Enhanced Level Set Segmentation by Soft Fuzzy C Means Clustering

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Abstract **– One of the major high-level tasks in computer vision is the process of object detection and recognition. During this process, it is crucial to separate different objects in a visual scene – the classical problem of Image Segmentation. The purpose of image segmentation is to partition an image into *meaningful* regions and objects (of related content) with respect to a particular application. Many algorithms have been elaborated for Image segmentation over the years but a correct or "desired" segmentation of an image is still not efficiently defined. This paper aims at developing a system which is the hybrid of two very efficient segmentation algorithms namely Fuzzy C-means clustering algorithm and Level set segmentation. The new algorithm automates the initialization and parameter configuration of the level set segmentation, using spatial fuzzy clustering.**

Keywords **– Segmentation, Clustering, Level-Set, Lab Color Space.**

I. Introduction

Image segmentation refers to partition an image into different significant components, regions and objects (of related content) with respect to a particular application, thus to facilitate the task at higher levels such as object detection and recognition. Visual image segmentation is the process by which the visual system, groups features that are part of a single shape. This correspondence is concerned with a method for image segmentation based on the Human Visual System (HVS) principle.

Many different Automatic Segmentation techniques have been developed and detailed surveys can be found in [2].The image segmentation approaches can be broadly divided into four categories: thresholding, clustering, edge detection and region extraction. In this paper, a clustering based method for image segmentation is considered and studies have shown that clustering techniques are proficient of image segmentation and determining certain region of interest [4]. There are several clustering algorithm proposed in the literature for segmentation.

Clustering is a process for classifying objects or patterns in such a way that samples of the same group are more similar to one another than samples belonging to different groups. Many clustering strategies have been used, such as the hard clustering scheme and the fuzzy clustering scheme, each of which has its own special characteristics.

The conventional hard clustering method restricts each point of the data set to exclusively just one cluster. As a consequence, with this approach the segmentation results are often very crisp, i.e., each pixel of the image belongs to exactly just one class. Fuzzy set theory produced the idea of partial membership of belonging described by a membership function; fuzzy clustering as a soft segmentation method has been widely studied and successfully applied in image segmentation [1]. Among the fuzzy clustering methods, fuzzy c-means (FCM) algorithm is the most popular method used in image segmentation because it has robust characteristics for ambiguity and can retain much more information than hard segmentation methods. The paper mainly focuses on the steps that are taken to segment an image and results are shown.

Here, bottom-up image segmentation is considered. That is, we ignore (top down) contributions from object recognition in the segmentation process and we expect to segment images without recognizing objects.

II. Preliminary Theory

Clustering:

Clustering deals with finding a structure in a collection of unlabeled data. It can be defined as "the process of organizing objects into groups whose members are similar in some way". A *cluster* is therefore a collection of objects which are "similar" between them and are "dissimilar" to the objects belonging to other clusters.

We consider three typical clustering partitioning algorithms, which are the k-Means, the Fuzzy C-Means and the Gaussian of Mixtures algorithm. We briefly review these methods:

A. K-means Clustering Algorithm

The procedure of K-means clustering algorithm follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. The main idea is to define k centroids, one for each cluster. This algorithm aims at minimizing an *objective function*, in this case a squared error function. The objective function can defined as:

$$J= \sum_{j=1}^{k} \sum_{i=1}^{n} ||x_i^{(j)}-v_j||^2 \qquad (1)$$

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Where $||x_i^{(j)}-v_j||^2$ is a chosen distance measure between a data point x_i and the cluster centre v_j, is an indicator of the distance of the *n* data points from their respective cluster centers. [4]

The K-means algorithm has been used for a fast and crisp "hard" segmentation. The Fuzzy Set theory has improved this process by allowing the concept of partial membership, in which an image pixel can belong to multiple clusters. This "soft" clustering allows for a more precise computation of the cluster membership, and has been used successfully for image clustering. Two factors have made the k-Means popular: it has linear time complexity and its easy implementation

B. Fuzzy C-Means Clustering Algorithm

Fuzzy c-means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. This method is frequently used in pattern recognition. The fuzzy C-means (FCM) algorithm follows the same principles as the K-means algorithm in that it compares the RGB value of every pixel with the value of the cluster center [3]. The main difference is that instead of making a hard decision about which cluster the pixel should belong to, it assigns a value between 0 and 1 describing "how much this pixel belongs to that cluster" for each cluster. Fuzzy rule states that the sum of the membership value of a pixel to all clusters must be 1. The higher the membership value, the more likely that pixel is to belong to that cluster. The FCM clustering is obtained by minimizing an objective function shown in equation (2):

$$J = \sum_{i=1}^{n} \sum_{k=1}^{c} \mu_{ik}{}^{m} \, |p_i - v_k|^2 \qquad (2)$$

Where J is the objective function, n is the number of pixels in the image E, c is the number of clusters, µ is the fuzzy membership value from table, m is a fuzziness factor (a value > 1), p_i is the ith pixel in E, v_k is the centroid of the kth cluster, $|p_i - v_k|$ is the Euclidean distance between p_i and v_k defined by equation (3):

$$|\, p_i - v_k \,| = \sqrt{\sum_{i=1}^{n} (p_i - v_k)^2} \qquad (3)$$

The calculation of the centroid of the kth cluster is achieved using equation (4):

$$v_k = \frac{\sum_{i=1}^{n} \mu_{ik}^{m} p_i}{\sum_{i=1}^{n} \mu_{ik}^{m}} \qquad (4)$$

The fuzzy membership table is calculated using the original equation (5):

$$\mu_{ik} = \frac{1}{\sum_{l=1}^{c} \left(\frac{|p_i - v_k|}{|p_i - v_l|} \right)^{\frac{2}{m-1}}} \qquad (5)$$

This algorithm has been extended for clustering of color images in the RGB color space. Hence, the computation given in equation (3) to compute the Euclidean distance between the values p_i and v_k is modified to incorporate RGB colors, and is shown in equation (6):

$$|p_i - v_k| = \sqrt{\sum_{i=1}^{n} (p_{iR} - v_{kR})^2 + (p_{iG} - v_{kG})^2 + (p_{iB} - v_{kB})^2} \qquad (6)$$

The standard FCM algorithms is optimized when pixels close to their centroids are assigned high membership values, while those that are far away are assigned low values [9].

C. Gaussian of Mixtures Algorithm (GM)

Another way to allow each pattern to belong to different clusters is by using the Gaussian of Mixtures algorithm. In this probabilistic model, each pattern is characterized by a set of Gaussian mixtures [5]:

$$P(x_i ; K) = \sum_{k=1}^{K} \pi_k g_k(x_i) \qquad (7)$$

where g_i is a Gaussian distribution and π_i a prior distribution ($\sum_k \pi_k = 1$). The model parameters and the cluster membership function are determined by maximizing the log-likelihood function:

$$l(K) = \sum_{i \in I} \log (p(x_i ; K)) \qquad (8)$$

where *I* is the whole image. This step is efficiently done by using the Expectation Maximization algorithm.

D. EM Algorithm

Expectation Maximization (EM) is one of the most common algorithms used for density estimation of data points in an unsupervised setting. The algorithm relies on finding the maximum likelihood estimates of parameters when the data model depends on certain latent variables. In EM, alternating steps of Expectation (E) and Maximization (M) are performed iteratively till the results converge. The E step computes an expectation of the likelihood by including the latent variables as if they were observed, and a maximization (M) step, which computes the maximum likelihood estimates of the parameters by maximizing the expected likelihood found on the last E step [6]. The parameters found on the M step are then used to begin another E step, and the process is repeated until convergence. Conceptually, The EM algorithm can be considered as a variant of the K Means algorithm where the membership of any given point to the clusters is not complete and can be fractional [6].

III. METHODOLOGY

Our algorithm - Hybrid segmentation using fuzzy C-means and level set segmentation: Figure.1 illustrates the flowchart of the proposed algorithm. To start with, the image which is to be segmented is fed to the algorithm. The algorithm will be described in stepwise manner as follows:

Step 1:

Convert into Lab color space:

We get a non uniform quantization of the color values in the CIE *L*a *b** space, so that regions having high density in the color space will benefit of a finer resolution, while areas with low density will have coarse resolution. *Lab* color is designed to approximate human vision. Its *L* component closely matches human perception of lightness. Clustering approach is employed on all the pixel values in CIELab color space.

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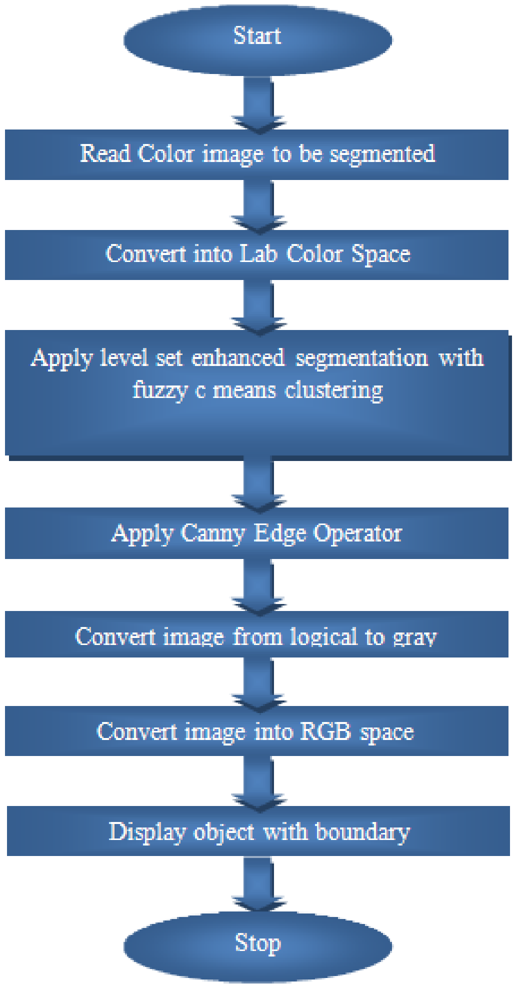

Fig.1. Flowchart for the hybrid segmentation method

Step 2:
Apply level set segmentation with fuzzy c-means clustering:

A. Fuzzy C-means clustering algorithm:

The Fuzzy C-means clustering algorithm allows the concept of partial membership, in which an image pixel can belong to multiple clusters. Fuzzy rule states that the sum of the membership value of a pixel to all clusters must be 1. The higher the membership value, the more likely that pixel is to belong to that cluster. This "soft“ and “fuzzy” clustering approach compared to “hard” and ”crisp” clustering, allows for a more precise computation of the cluster membership, and has been used successfully for image clustering and for the efficient segmentation of images. The fuzzy C-means (FCM) algorithm compares the RGB value of every pixel with the value of the cluster center.

B. Level set segmentation:

In contrast to FCM using pixel classification, level set methods utilize dynamic variational boundaries for image segmentation. Segmenting images by means of active contours is a well- known approach. The controlling parameters of level set segmentation are now derived from the results of fuzzy clustering directly. The new algorithm automates the initialization and parameter configuration of the level set segmentation, using spatial fuzzy clustering. It employs an FCM with spatial restrictions to determine the approximate contours of interest in an image.

Level set methods embed active contours into a time dependent PDE (partial differential equation) function $\Phi(t, x, y)$. It is then possible to approximate the evolution of active contours implicitly by tracking the zero level set $\Gamma(t)$ [7].

- $\Phi(t, x, y) < 0$ (x,y) *is inside* $\Gamma(t)$
- $\Phi(t, x, y) = 0$ (x,y) *is at* $\Gamma(t)$
- $\Phi(t, x, y) > 0$ (x,y) *is outside* $\Gamma(t)$

Active contour models are widely used in image Segmentation problems. By applying canny edge operator (available in Matlab) we can find edges in image based on contours. An edge in an image as a boundary or contour at which a significant change occurs in some physical aspect of the image. The motivation for Canny's edge operator was to derive an “optimal” operator in the sense that minimizes the probability of multiply detecting an edge, minimizes the probability of failing to detect an edge and minimizes the distance of the reported edge from the true edge. The first two of these criteria address the issue of detection, that is, given that an edge is present will the edge detector find that edge (and no other edges). The third criterion addresses the issue of localization that is how accurately the position of an edge is reported [10].
After getting segmentation the resultant image can be converted back into RGB color space to make it resemble with original image.

Step: 3
Display object with Boundary:

To get desired results of segmentation, segmented objects would be displayed with a boundary around them. In this step, curves are evolved in an image from initial locations, in response to information derived from the image, to detect object boundaries [8], active contours forces the level set function to be close to a signed distance function. (A boundary is a contour in the image plane that represents a change in pixel ownership from one object or surface to another). The height of the level set at a specific point as the value of the level set at a particular pixel, or Ø(x, y). Active contours are being used for image segmentation implicitly through the level set approach.

IV. Results

Results are shown in Figure 2 (‘a’ is original image and ‘b’ is segmented image). The described segmentation method can be performed over any set of real and synthetic images. The experimental results demonstrate the effectiveness of the proposed algorithm in segmenting objects and the improvement of the classical clustering approach- fuzzy c-means clustering.

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Experiments:

In order to measure the quality of the segmentations produced, three evaluation measures are considered:

- *Probabilistic Rand Index (PRI):* The PRI metric is in the range [0, 1], where high values indicate a large similarity between the segmented images and the ground-truth.
- *Variation of Information (VOI):* The VOI metric measures the sum of information loss and gain between two clusterings belonging to the lattice of possible partitions. The VOI measure is a distance, therefore the smaller it is, the closer the segmentation obtained and the ground-truth are.
- *Global Consistency Error (GCE):* GCE evaluates to what extent a segmentation can be viewed as the refinement of the other. The closer GCE is to zero, the better the segmentation with respect to the ground-truth.

(a) (b)

Fig.2. Segmentation Results

Table 1 shows average performance measures of these parameters on eight images taken from Berkeley Segmentation dataset. Traditional clustering algorithm (Fuzzy c-means [3]) has been considered to compare the performance of classical versus the new proposal. According to Table 1, we can draw the following remarks: Clearly, hybrid segmentation algorithm is the best method on the considered images. An interesting point is that FCM performs better than Hybrid for the PRI (higher → better) measure, and worst for the other two parameters VOI and GCE (lower → better). But the value of PRI is close to 1 which makes it justified. Comparison of PRI, VOI and GCE between the proposed algorithm and FCM algorithm is shown in the form of Bar graph in figure 3 which clearly depicts the performance of hybrid over FCM.

V. Conclusion

A new hybrid image segmentation algorithm is developed that segments objects from foreground, and the background surrounding it, will not be extracted. Values of several parameters improve the accuracy of image segmentation from the previous approaches. Image segmentation experiments are carried on real images and two of these test images are taken from the very popular Berkeley Segmentation Benchmark Dataset. It is fast and efficient method for color image segmentation. It is mainly designed to segment color images having bright contrasts. In future, this algorithm can be improved further to handle complex images and to be implemented in other color spaces also.

Table 1: Average of Eight Images

Average →	**PRI**	**VOI**	**GCE**
Hybrid	0.72	1.37	0.12
FCM	0.85	1.81	0.17

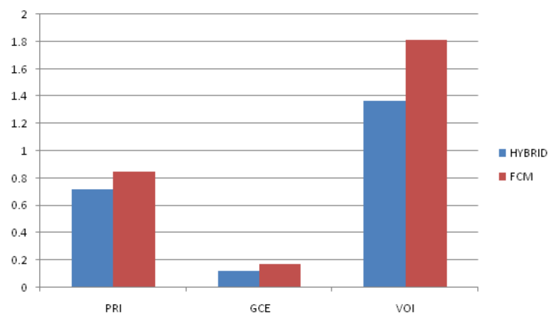

Fig.3. Comparison graph for Table 1

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