



# Genetic algorithm and self organizing map based fuzzy hybrid intelligent method for color image segmentation



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## ABSTRACT

The grouping of pixels based on some similarity criteria is called image segmentation. In this paper the problem of color image segmentation is considered as a clustering problem and a fixed length genetic algorithm (GA) is used to handle it. The effectiveness of GA depends on the objective function (fitness function) and the initialization of the population. A new objective function is proposed to evaluate the quality of the segmentation and the fitness of a chromosome. In fixed length genetic algorithm the chromosomes have same length, which is normally set by the user. Here, a self organizing map (SOM) is used to determine the number of segments in order to set the length of a chromosome automatically. An opposition based strategy is adopted for the initialization of the population in order to diversify the search process. In some cases the proposed method makes the small regions of an image as separate segments, which leads to noisy segmentation. A simple ad hoc mechanism is devised to refine the noisy segmentation. The qualitative and quantitative results show that the proposed method performs better than the state-of-the-art methods.

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## 1. Introduction

The fundamental purpose of color image segmentation is to divide or partition a color image into a set of disjoint non-overlapping regions (segments) such that each segment represents a particular object. Since last decades, abundance of techniques have been proposed to address the problem of an image segmentation. Although, color image segmentation is still considered as a challenging problem in computer vision research community. Particularly, the segmentation of colored natural images is the most difficult job because of the random inhomogeneities that exist in color and texture. Most of the approaches address the segmentation of a particular type of an image for particular application. Moreover, these approaches are not fully automatic and need a significant amount of user intervention to segment the objects of interest accurately.

In literature there are many color image segmentation techniques which can be divided into [1] image-domain based, physics based and feature-space based approaches. Image-domain based methods use both color and spatial features to carry out the segmentation task. The efficiency of these methods is depending on the selection of seed regions, which are normally set manually by the user. On the other hand the physics based methods use the physical models of material reflection to carry out color image segmentation [2]. It needs the reflection property of the underlying object which are not known in most of the cases and hence it is an application specific. The feature-based methods use color features only which leads to inaccurate results due to the lack of spatial relationship among the pixels [3].

Contour based segmentation algorithms can be found in literature [4–7]. It starts from an initial boundary in the form of a spline curve; the curve is iteratively evolved to minimize some energy function. It suffers from the manual initialization of the curve or boundary to the object of interest. It is trapped in local optima and leads to unsatisfactory results. Markov random field based on statistical models [8] uses spatial connectivity information among the neighboring pixels to perform segmentation. Graph cut [9–12] is another segmentation approach based upon Markov random fields. These algorithms solve a two class problem, i.e., separating the background and foreground objects. Watershed segmentation

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[13,14] has been successfully adopted for the two class segmentation problems. It often produces bad results for image having many regions.

Image segmentation can be treated as a clustering problem. The feature of each pixel corresponds to a pattern and the combination of the pixels (i.e. segment) corresponds to a cluster. Keeping this analogy in mind, many clustering algorithms have been used for image segmentation [15–18]. Among them K-means [15] is the basic clustering algorithm adopted for color image segmentation. Similarly, fuzzy C-means (FCM) [16] has been used for image segmentation extensively. It is a clustering process which decrease intra clusters distances and increase inter clusters distances. However, its implementation faces three problems: (1) cluster initialization, (2) determining number of the clusters, and (3) lacking of the robust cluster validity index. The performance of the algorithm depends on the initialization of clusters centroids. If the cluster centroids represent the search space uniformly then the results will be better on the other hand the biased initialization will lead to poor performance. Similarly the number of clusters have considerable impact on the quality of segmentation. The clustering validity index (CVI) performs a vital role in the process of image segmentation and data clustering [19]. It checks whether the provided clustering or grouping of the given data reflects the original structure of the data or not. The cluster validity index (CVI) adopted for the FCM takes into account both compactness and separation for reliable segmentation. Note that if the first (i.e., compactness) is adopted as a cluster validity index then the best result would contain the cluster/segments number as that of the number of points present in the underlying search space. Similarly if the second (i.e., separation) is considered as a cluster validity index then the best result would contain only one segment/cluster. The CVI that combines compactness and separation is insufficient to represent the geometrical structure of the data because it normally finds the distances between the centroids of different clusters.

In this paper, a fixed length fuzzy genetic algorithm (GA) is used to perform color image segmentation. A new objective function or clustering validity index (CVI) is proposed which incorporate the fuzzy compactness of data points and fuzzy separation of the segments centroids. In the new objective function, the compactness is defined term of fuzzy deviation of data points while the separation is based on the average variance of segments centroids. A self organizing map (SOM) is used to determine the optimal number of segments in order to set the length of a chromosome. In some cases the proposed method makes some small regions of an image as separate segments which leads to noisy segmentation. A simple merging technique is proposed to address this problem and make segmentation refine. All the operations are performed in the Lab color space, which is near to the human level of perception. The block diagram of the proposed method is given in Fig. 1.

The rest of the paper is organized as follows. Section 2 presents a mechanism to set the length of a chromosome automatically. In Section 3 the GA based color image segmentation is discussed. Section 4 presents the detail of the merging algorithm to handle the over-segmentation problem. Experimental results are discussed in Section 5 followed by the conclusion.

## 2. Determining length of the chromosome

We have used a fixed length genetic algorithm in which the length of a chromosome depends on the number of segments. Generally in segmentation algorithms the number of segments is set by user manually using some sort of domain knowledge. In this work a self organizing map (SOM) [20] is used to determine the number of segments that are hiddenly present in the underlying distribution (input image).

SOM is an unsupervised type of artificial neural network (ANN) which is used to produce the low dimensional map of complex input space. Here we use a two-dimensional (2D) SOM network that consists of nodes or cells. Each node  $N_i$  of the SOM, where  $i \in 16$ , is assigned a weight vector ( $\vec{w}_i$ ) having three elements. The training dataset (in the form of input image) is organized as a vector  $\vec{V}_j$  in a raster scanning manner, where  $j = 1, \dots, N$  and  $N$  represents the total number of pixels in the input image. Note that each element of the  $\vec{V}_j$  (training set) consists of the three channels of the input image.

The SOM network is randomly initialized. Then each input vector is iteratively feeded to the SOM network. The input vector is assigned to a best matching unit (BMU), a node in the SOM network which has maximum similarity to the given input vector. The best matching unit (BMU) to a given input vector  $\vec{V}_j$  is determined by using the following Eq. (1).

$$BMU = \underset{i \in \{1, 16\}}{\operatorname{argmin}} \|\vec{V}_j - \vec{w}_i\|, j \in [1, N] \quad (1)$$

where 16 is the number of nodes/cells in the SOM network. Here, 16 is to be considered the maximum number of segment  $s$  present in a particular image. The weights of  $N_{BMU}$  (a node in the network which has maximum matching to the input vector  $\vec{V}_j$ ) and its neighboring nodes are updated using Eq. (2)

$$\vec{w}_i(t+1) = \begin{cases} \vec{w}_i(t) + \Psi(t)\zeta(t)[\vec{V}_j(t) - \vec{w}_i(t)], & \text{if } \|N_{BMU} - N_i\| \leq \nu(t) \\ \vec{w}_i(t), & \text{if } \|N_{BMU} - N_i\| > \nu(t) \end{cases} \quad (2)$$

In Eq. (2)  $t$ , and  $\nu(t)$  represent the iteration step and the neighborhood radius of the network respectively. Initially the neighborhood radius  $\nu_0$  is kept high to cover all the nodes of the network. Then

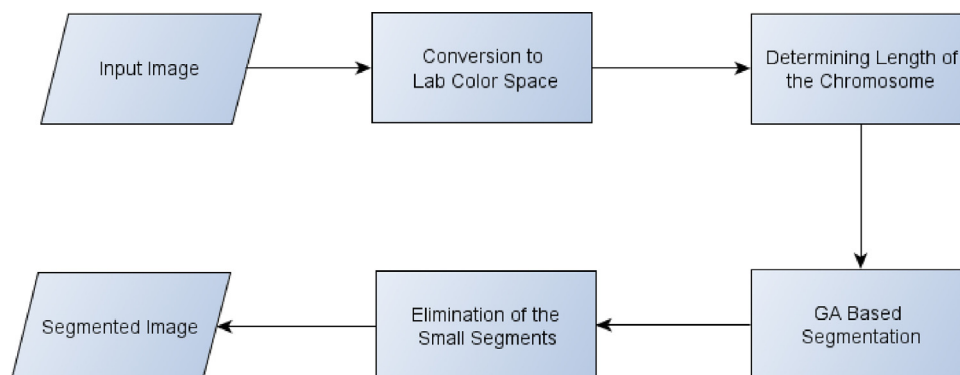


Fig. 1. Block diagram of the proposed method.

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