

Modal and Mutational Agglomeration based Automatic Colour Image Segmentation

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Abstract— We have proposed an efficient approach for unsupervised colour image segmentation that segments an image into its constituent parts automatically. The aim of this algorithm is to produce precise segmentation of images using intensity information along with neighbourhood relationships. Here automatic hierarchical modal and mutational agglomeration based cluster of images takes place. In addition, Cluster ensemble has been utilized for introducing a robust technique for finding the number of components in an image automatically. The proposed algorithm is very simple in implementation, fast in encoding time. Experimental results shown that the algorithm generates good quality segmented image.

Keywords- Clustering; Segmentation; Thresholding; Modal Analysis; Mutational Agglomeration.

I. INTRODUCTION

Segmentation refers to the process of partitioning a digital image into multiple segments or regions. The goal of segmentation is to simplify the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries in images [1]. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. Image segmentation is a very important field in image analysis object recognition, image coding and medical imaging. Segmentation is very challenging because of the multiplicity of objects in an image and the large variation between them. Image segmentation is the process of division of the image into regions with similar attributes. In many object based image segmentation applications, the number of cluster is known a priori, but our proposed scheme is automatically determined the number of cluster which is produced the segmentation of images. The proposed technique should be able to provide good results whereas K-means algorithm which may get stuck at values which are not optimal [18]. Some of the several unsupervised clustering algorithms developed include K-means [7,8], fuzzy K-means, ISODATA [12], self-organizing feature map (SOM) [10], Particle Swarm Optimization (PSO) [9], Learning Vector Quantizers (LVQ) [11], GA based Clustering [5] etc.

This paper presents automatic hierarchical image segmentation of color images using Modal Analysis and Mutational Agglomeration based clustering. One natural

view of segmentation is that we are attempting to determine which components of a data set naturally “belong together”. Clustering is a process whereby a data set is replaced by clusters, which are collections of data points that “belong together”. Thus, it is natural to think of image segmentation as image clustering i.e. the representation of an image in terms of clusters of pixels that “belong together”. The specific criterion to be used depends on the application. Pixels may belong together because of the same color or similarity measure. The result of this algorithm produced a better result to compare with other techniques. Various segmentation techniques have been developed for image segmentation [2,14,15,17].

The rest of this paper is organized as follows: - Section II, the concepts of clustering is provided. Section III describes the threshold method. Section IV gives the concepts of modal analysis and section V gives the concepts of mutational agglomeration and section VI describe the proposed algorithm and section VII described the experimental results and section VIII concludes the paper.

II. CLUSTERING

The process of grouping a set of physical or abstract objects into classes of similar objects is called clustering. A cluster is a collection of data objects that are similar to one another within the same cluster and are dissimilar to the objects in other clusters. By clustering, one can identify dense and sparse regions and therefore, discover overall distribution patterns and interesting correlations among data attributes.

Clustering may be found under different names in different contexts, such as unsupervised learning (in pattern recognition), numerical taxonomy (in biology, ecology), typology (in social sciences) and partition (in graph theory) [3]. By definition, “cluster analysis is the art of finding groups in data”, or “clustering is the classification of similar objects into different groups, or more precisely, the partitioning of a data into subsets (clusters), so that the data in each subset (ideally) share some common trait-often proximity according to some defined distance measure” [4]. Clustering is a challenging field of research as it can be used as a stand-alone tool to gain insight into the distribution of data, to observe the characteristics of each cluster, and to focus on a particular set of clusters for further analysis. Alternatively, cluster analysis serves as a pre-processing step

for other algorithms, such as classification, which would then operate on detected clusters.

Hierarchical agglomerative clustering techniques start with as many clusters as there are unique values. Then pairs of cluster are successively merged till the optimal number of clusters is reached, depending on the termination condition. Termination condition is to be chosen carefully; else the hierarchical agglomerative clustering technique will ultimately yield one cluster containing all the values [16].

Clustering is a useful unsupervised data mining technique which partitions the input space into K regions depending on some similarity/dissimilarity metric where the value of K may or may not be known a priori. The main objective of any clustering technique is to produce a $K \times n$ partition matrix $U(X)$ of the given data set X, consisting of n patterns, $X = \{x_1, x_2, \dots, x_n\}$ [13].

III. THRESHOLDING

Thresholding refers to the selection of a range such that if a pixel is within the threshold distance from a known centroid then the pixel is said to belong to that centroid's cluster. For any pixel x, the membership to a cluster centroid, C_i is defined as

$$C_i = \{x: x \in f(x,y) \text{ and } |I(C_i) - I(x)| \leq T\},$$

Where C_i = ith cluster centroid,

x = pixel under consideration,

$I(C_i)$ = Intensity value of ith centroid,

$I(x)$ = Intensity value of the pixel x,

T = Threshold value,

$f(x,y)$ = Input image.

In the proposed algorithm the threshold value is taken to be 5. Now, a 5×5 image with pixel values as shown in given below. Assume the three known centroids are 26, 80 and 134 respectively. We denote their cluster membership as I, II and III respectively.

26	30	134	138	82
26	30	130	136	83
25	26	129	135	80
24	26	129	135	80
23	29	132	133	81

The corresponding membership pattern is as shown in below.

I	I	III	III	II
I	I	III	III	II
I	I	III	III	II
I	I	III	III	II
I	I	III	III	II

The value of the threshold is selected as 5 for natural images based on experimental results.

IV. MODAL ANALYSIS

In traditional k-means, the new centroid value is computed as the mean of the pixel values of all the pixels that belong to a particular cluster.

By modal analysis, the mode of the distribution of the pixel values of a cluster is calculated instead of the mean. The new centroid is taken as the pixel value that is repeated the highest number of times in the cluster (mode).

The basis of modal analysis stems from the fact that the mode is a more robust representative of the cluster than the mean and so a single very unrepresentative pixel in a cluster will not affect the mode value, which will affect the mean value significantly. Since the mode value must actually be the value of the pixel occurring the maximum number of times in the cluster, the modal analysis does not create new unrealistic pixel values when there is wide variation in pixel values. Thus new intensity is never generated. Suppose, for a cluster of 1000 pixels, the following distribution obtained.

Pixel Intensity Value	No. of Pixels
10	12
11	50
12	298
13	51
14	24
15	2
16	32
17	33
18	22
19	14
20	100
21	90
22	84
23	70
24	60
25	58

Collect all the pixels of the each cluster which is defined by threshold operation. Find occurrence of each pixels in $occur(m,n)$, where $m = 1,2,\dots$ ith pixels and $n = 1$ and 2 . Now, $occur(x,1) = \{ I(x) : \text{pixel intensity for any pixel } x \}$ and $occur(x,2) = \{ O(x) : \text{no. of times pixel } x \text{ is repeated in that group or cluster} \}$. Find the pixel x that $O(x)$ is maximum and corresponding $I(x)$ is selected for the centroid's of that cluster.

For an example, here $occur(1,1) = 10$ (pixel intensity) and $occur(1,2) = 12$ (no. of pixels with intensity 10), $occur(2,1) = 11$, $occur(2,2) = 50$, $occur(3,1) = 12$, $occur(3,2) = 298$ and so on.

Here the **mode** value is: 12 with frequency of occurrence 298 i.e. $occur(3,2) = 298$ which is the maximum. The **mean**

value is: 17.25 with frequency of occurrence 33. For this reason, mode is a better choice than mean.

V. MUTATIONAL AGGLOMERATION

In the mutational agglomeration phase, the individual groups are compared at the bit level. Each group's centroid i.e. the pixel that is maximally distributed in the group is converted to its binary equivalent. They are then XORed with one another in order to find the positions where they are similar.

Suppose the following represent two centroids' binary equivalent:

Centroid 1 → 11101010
Centroid 2 → 11100101

As shown, the two groups are same if the two centroids' atleast four Most Significant Bits (MSB) are same. This can be easily established by XORing the two values and counting the number of 0's from MSB as given below.

Centroid 1 → 11101011
Centroid 2 → 11100101

 00001110

If above condition is true, then merge the two groups into one and replace the two centroids by one value based on modal analysis of all the pixels in the resulting centroid's cluster.

For an example, consider the following 4 centroids.

Centroid 1: 11001110
Centroid 2: 11001111
Centroid 3: 11100101
Centroid 4: 01100101

Here, Centroid 1 and Centroid 2 are similar in four most significant bits. Centroid 3 and Centroid 4 differ by 1 bit in MSB as shown above.

By mutational agglomeration only combine Centroid 1 and Centroid 2, since they are similar in the 4 most significant bits. Replace Centroid 1 and Centroid 2 by the modal value of all the pixels of their corresponding clusters, say by 11001110. New centroids will be:

Centroid 1: 11001110
Centroid 3: 11100101
Centroid 4: 01100101

VI. PROPOSED ALGORITHM

An image is a spatial representation of an object and represented by a matrix of intensity value. It is sampled at points known as pixels and represented by color intensity in RGB color model. A basic color image could be described as three layered image with each layer as Red, Green and Blue as shown in Fig. 1.

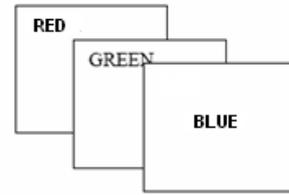


Fig. 1: Image Components

The proposed algorithm takes as input any 24-bit color image of any arbitrary dimension. A 24-bit color image has R,G and B components. It automatically segments them into optimal no of segments, which in turn, is determined by the nature of the image itself. The algorithm is as follows:

- Step 1:** Take a color image $f(x,y,z)$ as input; z represents the component (R, G or B).
- Step 2:** For each component R, G and B of the image, do the **Steps 3 to 6**.
- Step 3: Thresholding**
For each and every pixel of the component array $f(m,n,component)$ of the image, where $m=1$ to row, $n=1$ to column, compare them to find similarity (a maximum deviation of +/-5) as noted in section III.
 - 3.1: If true, put them in the same group.
 - 3.2: Else, form a different group.
- Step 4: Modal Analysis**
For each and every group, find the mode of all The pixel values belonging to the Group. The pixel with maximum mode will be new centroid of the group as discussed in section IV.
- Step 5: Mutational Agglomeration**
 - 5.1: Convert the centroids pixel values to their binary equivalent.
 - 5.2: Compare the 4 most significant bit positions
 - 5.2.1: If they are same, merge the group.
 - 5.2.2: Else, the groups are kept separate as before.
 - 5.3: Repeat the **Step 5** till the deviation between The previously established groups and the new groups formed are least or does not exist.
- Step 6: Replacing Segmented Clusters**
Replace the image pixel values of the component with the centroid of the group values to which they belong.

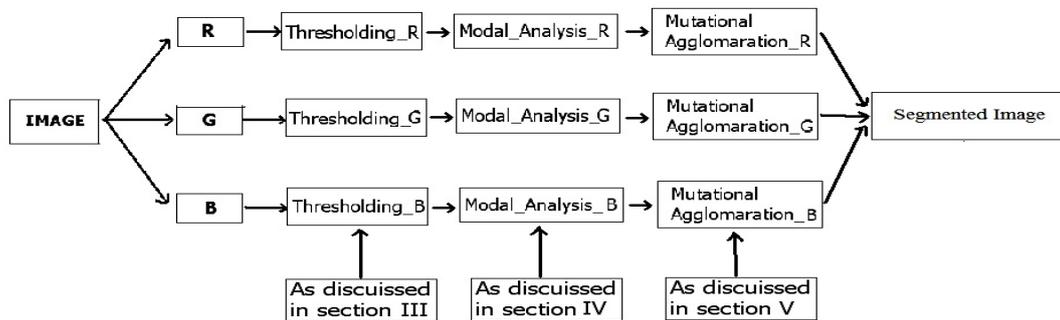


Fig.2: Major Steps in our Clustering technique

VII. EXPERIMENTAL RESULTS

The algorithm developed has been simulated using MATLAB. The input images are considered to be .bmp, .tif, .jpg and .png images. The precision is assumed to be 24 i.e. the no. of bits per pixel is 24 with components R, G and B each having length of 8 bits. All the images files that we have tested are natural images. The no. of segments obtained is tabulated in Table I. The segmented images using the proposed algorithm are shown in Fig.3.

All the results have been reported in Table I. These results have been compared to those of SOM and DCPSO [6] and to that of snob [2]. The optimal range for the number of clusters for the images of Lena, mandrill and peppers has also been copied from [2] which are based on visual analysis by a group of ten people. The optimal range for the satellite image (cal) has been estimated by the authors.

VIII. CONCLUSION

This paper presented a new approach for unsupervised segmentation for Colour image that can successfully segment the images. In this paper, that the user does not need to predict the optimal number of clusters, required to partition the dataset, in advance. Comparison of the experimental results with that of other unsupervised clustering methods, show that the technique gives satisfactory results when applied on well known natural images. Moreover results of its use on images from other fields (MRI, Satellite Images) demonstrate its wide applicability.

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TABLE I. EXPERIMENTS ON NATURAL IMAGES

Image	Optimal Range	Proposed Method	DCPSO using V	SOM	snob
Lena	5 to 10	8	6.85	20	31
Mandrill	5 to 10	8	6.25	20	42
peppers	6 to 10	8	6	20	39
Jet	5 to 7	6	5.3	14	22
MRI	3 to 7	7	-	-	-
Cal	4 to 8	6	-	-	-
Pangong	-	8	-	-	-
Lady	-	8	-	-	-
Sunset	-	7	-	-	-
Zelda	-	6	-	-	-



(a)

(b)



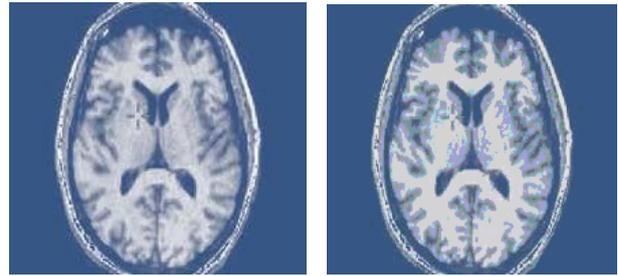
(c)

(d)



(e)

(f)



(g)

(h)



(i)

(j)

Fig.3: The demonstration of the test images : (a),(c),(e),(g) and (i)- Original image and (b),(d),(f),(h) and(j)- Segmented image by proposed method.