Improved Color Image Segmentation by Using Extended FCM Clustering

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ABSTRACT:

Color image has the potential to convey more information than monochrome or gray level images, RGB color model is used in many applications of image processing and image analysis such as Image Segmentation. The standard approaches to image analysis and recognition beings by segmentation of the image into regions (objects) and computing various properties and relationships among these regions. Image segmentation algorithms, have been developed for extracting these regions. Due to the inherent noise an degradation of the input cues to the algorithm , meaningful image segmentation is difficult process. However, the regions are not always defined, it is sometimes more appropriate to regard them as fuzzy subjects of the image. In this work the way is described an algorithm, which are used to segmentation of color images with clustering methods. This algorithm is tested on ten different color images, which are firstly transformed to R*B*G* color space. Conditions, results and conclusions are described lower. The results are compared using both Mahalanobis and Euclidean distances in the clustering algorithm.

المستخلص:

الصورة الملونة لديها القدرة على ايصال المعلومات اكثر من مستوى الاحادية والصورة الرمادية. إن نظام الالوان RGB يعتبر النظام الاكثر استخداما في تطبيقات معالجة وتحليل الصور الملونة مثل عملية تقطيع الصور الى مناطق محددة .

المنهج القياسي لتحليل الصور يبدأ بعملية تقطيع الصورة الى مناطق معينة ومن ثم ايجاد او حساب الخصائص والعلاقات بين هذه المناطق. خوارزميات تقطيع الصور صممت لا يجاد واستخلاص هذه المناطق في الصورة ,بسبب الضوضاء الملازمة وتأثيرها على الصورة المدخلة تظل عملية التقطيع هذه اكثر صعوبة وتحديا كبيرا ,لذلك المناطق لا يمكن دائما ايجادها بسهولة في الصورة ويمكن اعتبارها اشياء غامضة ومضببه .

في هذا البحث تم تصميم نظام او خوارزمية لتقطيع الصورة الملونة باستخدام طريقة العنقدة (عناقيد) ,حيث تم تجريب هذه الخوارزمية على عدة صور ملونة مختلفة تبدا من استخدام النظام اللوني RGB . الشروط و النتائج والاستنتاجات تم وصفها

وذكرها في البحث , والنتائج تم مقارنة النتائج بين طريقتين لحساب المسافة بين العناقيد ومراكزها الاولى تسمى الاقليدية والثانية تسمى Mahalanobis المستخدمة في العناقيد.

1.1 INTRODUCTION:

Image segmentation was, is and will be a major research topic for many image processing researchers. The reasons are obvious and applications endless: most computer vision and image analysis problems require a segmentation stage in order to detect objects or divide the image into regions which can be considered homogeneous according to a given used in biomedical areas such as in the identification of lung diseases, in automated classification of white blood cells, in the detection of cancerous cells and in chromosome karyotyping. The application of image segmentation are numerous. Image segmentation has been[1]

Clustering is the search for distinct groups in the feature space. It is expected that these groups have different structures and that can be clearly differentiated. The clustering task separates the data into number of partitions, which are volumes in the n-dimensional feature space. These partitions define a hard limit between the different groups and depend on the functions used to model the data distribution.

1.2 Image segmentation

To humans, an image is not just a random collection of pixels; it is a meaningful arrangement of regions and objects. There also exits a variety of images: natural scenes, paintings, etc. Despite the large variations of these images, humans have no problem to interpret them. Considering the large databases on the WWW, in our personal photograph folders, a strong and automatic image analysis would be welcome.[2]

Image segmentation is the division of image into different region, each region having certain properties. It is critical component of an image recognition system because errors in segmentation might propagate to further processing steps such as feature extraction and classification.

Image segmentation is the first step in image analysis and pattern recognition. It is a critical and essential component of image analysis system, is one of the most difficult tasks in image processing, and determines the quality of the final result of analysis. Image segmentation is the process of dividing an image into different regions such that each region is homogeneous.

One natural view of segmentation is to identify regions of an image that have common properties while separating regions that are dissimilar .this is a problem known as clustering. Classical clustering assigns each object to exactly one class, whereas in fuzzy clustering the objects are assigned different degrees of membership to the different classes. Fuzzy clustering is an interactive approach of segmentation of image using principles of both cluster analysis and fuzzy logic. Image segmentation methods can be categorized as follows:

1. **Histogram thresholding:** assumes that images are composed of regions with different gray (or color) ranges, and separates it into a number of peaks, each corresponding to one region.
2. **Edge-based approaches:** use edge detection operators such as Sobel, Laplacian for example. Resulting regions may not be connected, hence edges need to be joined.
3. **Region-based approaches:** based on similarity of regional image data. Some of the more widely used approaches in this category are: Thresholding, Clustering, Region growing, Splitting and merging.
4. **Hybrid:** consider both edges and regions.

The project is done using Image Segmentation by fuzzy Clustering. It is based on color image segmentation using Mahalanobis distance. Euclidean distance is also used for comparing between the quality of segmentation between the Mahalanobis and Euclidean distance.[3]

1.3 Image Segmentation by Clustering

Clustering is a classification technique. Given a vector of N measurements describing each pixel or group of pixels (i.e., region) in an image, a similarity of the measurement vectors and therefore their clustering in the N-dimensional measurement space implies similarity of the corresponding pixels or pixel groups. Therefore, clustering in measurement space may be an indicator of similarity of image regions, and may be used for segmentation purposes.

The vector of measurements describes some useful image feature and thus is also known as a feature vector. Similarity between image regions or pixels implies clustering (small separation distances) in the feature space. Clustering methods were some of the earliest data segmentation techniques to be developed.[7]

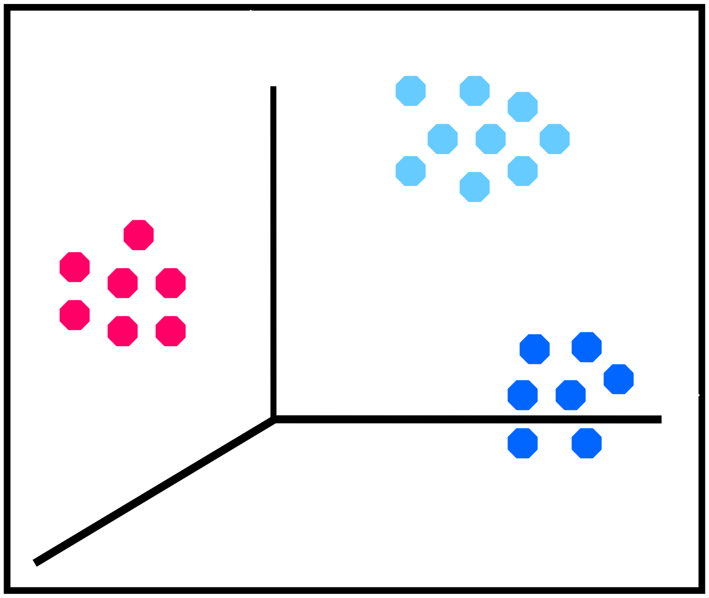

Figure 1 : shows similar data points grouped together into clusters.

Most popular clustering algorithms suffer from two major drawbacks:

- **First**, the number of clusters is predefined, which makes them inadequate for batch processing of huge image databases.
- **Secondly**, the clusters are represented by their centroid and built using an Euclidean distance therefore inducing generally an hyperspheric cluster shape, which makes them unable to capture the real structure of the data.

This is especially true in the case of color clustering where clusters are arbitrarily shaped

1.4 Clustering Algorithms

There are many type of clustering algorithms can be used in image segmentation and classification such as :

- K-means
- C-Mean
- Gustafson- Kessel
- K-medoids
- Hierarchical Clustering

C-means algorithm was used in the project and the distances were calculated using Mahalanobis and Euclidean distances

1.5 EFCM Clustering Overview

The Extended Fuzzy C-means clustering algorithm is based on the minimization of an objective function called C-means functional. C-Mean clustering follows the same principles as the K-means in that it compares the RGB value of every pixel with the value of the cluster center. 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[2]. The EFCM clustering is obtained by minimizing an objective function shown in equation (1):

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

Where:

- J is the objective function.
- n is the number of pixels in the entire image .
- c is the number of clusters .
- μ is the fuzzy membership value .
- m is a fuzziness factor (a value > 1).
- p_i is the i'th pixel in E
- v_k is the centroid of the k'th cluster
- $|p_i - v_k|$ is the Euclidean distance between p_i and v_k defined by equation (2):

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

The calculation of the centroid of the kth cluster is achieved using equation (3):

$$v_k = \frac{\sum_{i=1}^{n}\mu_{ik}^{m}p_i}{\sum_{i=1}^{n}\mu_{ik}^{m}} \qquad \text{........................... (3)}$$

The fuzzy membership is calculated using the original equation (4):

$$\mu_{ik} = \frac{1}{\sum_{i=1}^{c}\left(\frac{|p_i - v_k|}{|p_i - v_k|}\right)^{\frac{2}{m-1}}} \quad \text{............................ (4)}$$

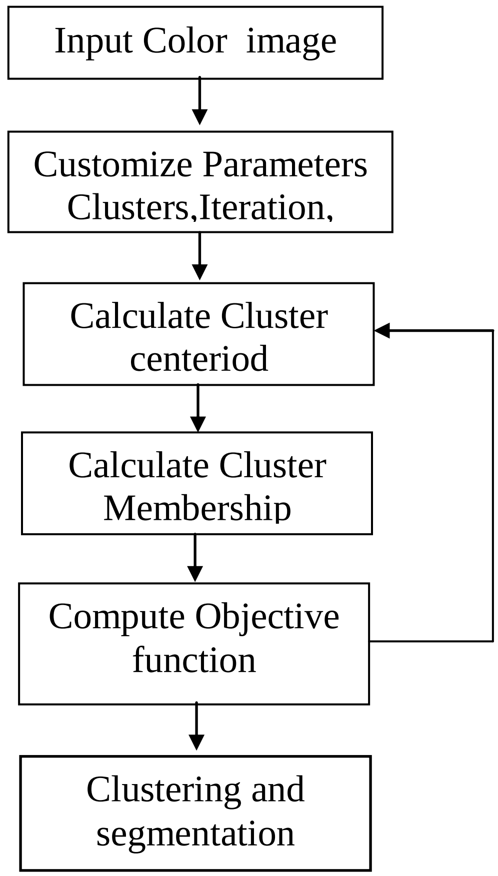

Figure 2 : shows Block Diagram to Proposed System EFCMC

1.5.1 C-Means Algorithm Properties

- There are always K clusters.
- There is always at least one item in each cluster.
- The clusters are non-hierarchical and they do not overlap.
- Every member of a cluster is closer to its cluster than any other cluster because closeness does not always involve the center of clusters.

1.5.2 C-Means Algorithm Process

- Step 1: Set the number of clusters, the fuzzy parameter (a constant > 1), and the stopping condition
- Step 2: Initialize the fuzzy partition matrix
- Step 3: Set the loop counter k = 0
- Step 4: Calculate the cluster centroids, calculate the objective value J
- Step 5: For each pixel, for each cluster, compute the membership values in the matrix
- Step 6: If the value of J between consecutive iterations is less than the stopping condition, then stop; otherwise, set k=k+1 and go to step 4
- Step 7: clustering and segmentation

1.6 How the problem was approached

Step 1: an image is taken as an input. The input image is in the form of pixels and is transformed into a feature space (RBG).

Step 2: Next similar data points, i.e. the points which have similar color, are grouped together using any clustering method.

A clustering method such as c-means clustering is used to form clusters as shown in the figure2 . The distances are calculated using Mahalanobis and Euclidean distant.

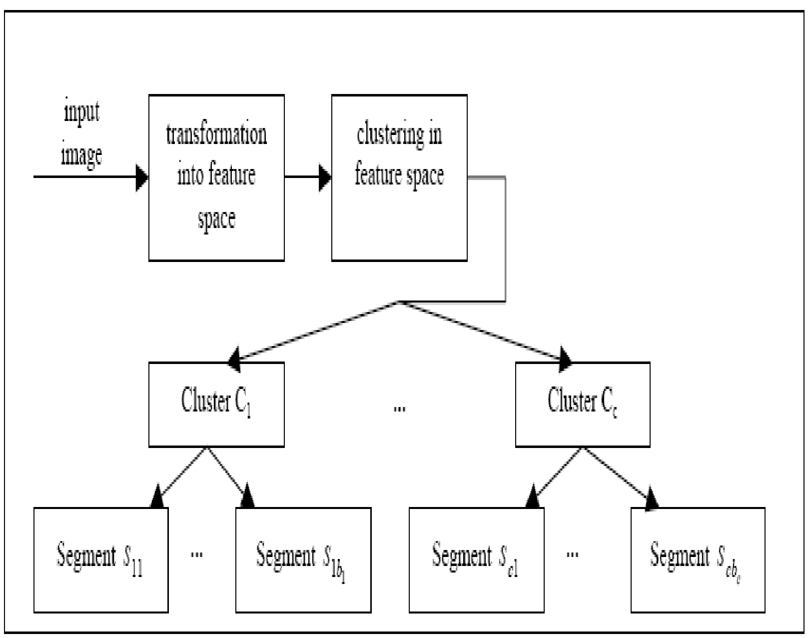

Figure 3 :Flow-chart of an image segmentation method

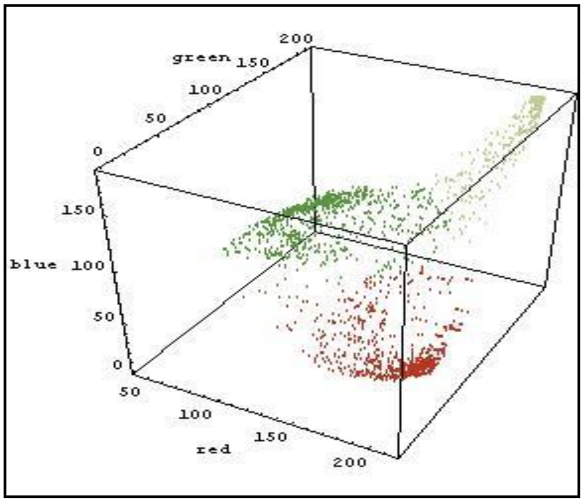

Figure 4 : shows how the data points are clustered in the 3-d RGB space

As one can see all similar colors are grouped together to form a cluster. The data points with minimum Mahalanobis distance or Euclidean distance are grouped together to form the clusters. Mahalanobis and Euclidean are described later below.

Step 3: After clustering is done, the mean of the clusters is taken. Then the mean color in each cluster is calculated to be remapped onto the image.

1.7 How Mahalanobis and Euclidean distance is calculated

Classical C-Mean and K-Mean clustering are used the Euclidean method to computing the distance. IN this work both Mahalanobis and Euclidean distances are described below clearly.

1.7.1 Mahalanobis Distance

There are a number of properties that can be summed up as follows:

- Mahalanobis Distance is a very useful way of determining the ”similarity” of a set of values from an ”unknown”: sample to a set of values measured from a collection of ”known” samples
- Superior to Euclidean distance because it takes distribution of the points (correlations) into account
- Traditionally to classify observations into different groups

- It takes into account not only the average value but also its variance and the covariance of the variables measured
- It compensates for interactions (covariance) between variables
- It is dimensionless

The formula used to calculate Mahalanobis distance is given below.

$$Dt(x) = (x - Ci) * Inverse(S) * (x - Ci) \quad \text{............................} (5)$$

Where:

The **X** is a data point in the 3-D RGB space**, Ci** is the center of a cluster.

S is the covariance matrix of the data points in the 3-D RGB space Inverse(S) is the inverse of covariance matrix S.

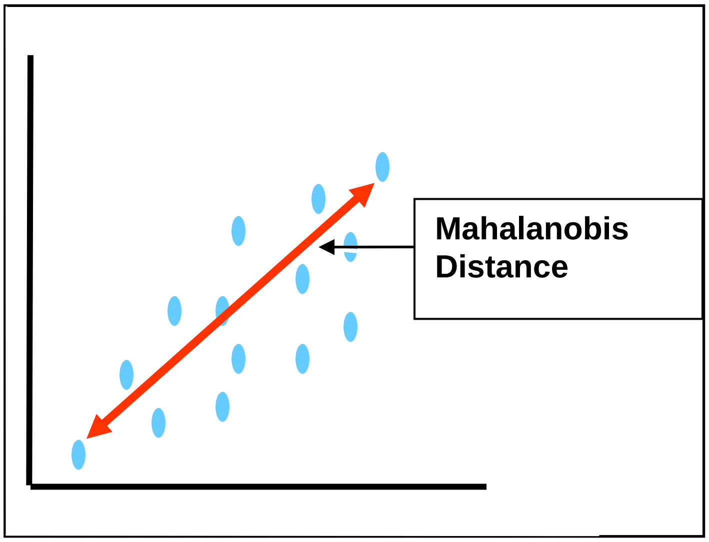

Figure 5 : shows how the Mahalanobis distance is calculated considering the variances of the data points in the 3-D RGB space.

1.7.2 Euclidean Distance:

The Euclidean distance is the straight-line distance between two pixels.

$$\text{Euclidean distance} = \sqrt{(x1 - x2)^2 + (y1 - y2)^2}\ , \quad \text{............................} (6)$$

where (x1,y1) & (x2,y2) are two pixel points or two data points.

In C-Mean clustering the distance has been calculated bases on equation 2:

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

The only difference between Mahalanobis and Euclidean distance is that Mahalanobis considers the Inverse of the covariance matrix of the set of data points in the 3-d space.

So,

Mahalanobis distance = $(P_i - V_k) * INV(Cov(S)) * (P_i - V_k)'$ .... (7)

Euclidean distance = $(P_i - V_k) * (P_i - V_k)'$ .... (8)

Here P_i is a data point and V_k is the center of a cluster.

S is a vector containing all the data points the 3-d color space.

1.8 Result and Discussion

Different color images have been tested by the proposed system EFCMC using Mahalanobis distance as shown in the below figures(6-9) and compared with the results (segmented images) obtained by the EFCMC using Euclidean distance.

a- Original Image (peppers) b- segmented image

Figure 6: show a- original image b- segmented image with 6-clusters by proposed system EFCMC using Mahalanobis distance

(a) (b) (c)

Figure 7: shown (a) Canary Original Image (b) Segmented Image using EFCMC by Mahanalobis distance with 3-clusters and (c) Canary Segmented Image using K-mean by Euclidean distance with 3-clusters.

(a) (b) (c)

Figure 8: shown (a) Parrot Original Image (b) Segmented Image using EFCMC by Mahanalobis distance with 6-clusters and (c) Parrot Segmented Image using K-mean by Euclidean distance with 6-clusters.

(a) (b) (c)

Figure 9: shown (a) Color Pepper Original Image (b) Segmented Image using EFCMC by Mahanalobis distance with 12-clusters and (c) Color Pepper Segmented Image using K-mean by Euclidean distance with 12 -clusters.

Table 1:Shows the quality measures for 10 color images after application the proposed system (EFCMC) consist No. of Clusters =3 , Max Iteration =20 and Precision= 0.00001

Image	Clusters	Iteration	Precision	Duration (minute)	PSNR
Canary	3	15	0.00001	0.15.29	30.749
Parrot	3	15	0.00001	0.53.13	30.966
Peppers color	3	20	0.00001	0.26.09	30.560

Table 2:Shows the quality measures for color image after application the proposed system (EFCMC) consist No. of Clusters =6 , Max Iteration =25 and Precision=0.00005

Image	Clusters	Iteration	Precision	Duration (minute)	PSNR
Canary	6	21	0.00005	1.26.58	31.052
Parrot	6	25	0.00005	1.26.16	31.305
Peppers color	6	22	0.00005	1.20.09	32.931

Table 3:Shows the quality measures for color images after application the proposed system (EFCMC) consist No. of Clusters =12 , Max Iteration =30 and Precision=0.00001

Image	Clusters	Iteration	Precision	Duration (minute)	PSNR
Canary	12	26	0.00001	3.34.05	34.010
Parrot	12	28	0.00001	4.06.74	33.788
Peppers color	12	28	0.00001	2.58.12	34.875

Table 4: Shows the quality measures for color images after application EFCMC using Mahalanobis and K-Mean using Euclidean distance .

Image	Clusters	EFCMC (Mahalanobis)		K-Mean (Euclidean)	
		Iteration	PSNR	Iteration	PSNR
Canary	3	15	30.749	8	29.419
Parrot	3	15	30.966	12	29.314
Peppers color	3	20	30.560	10	29.073

Table 5 :Shows the quality measures for color images after application EFCMC using Mahalanobis and K-Mean using Euclidean distance .

Image	Clusters	EFCMC (Mahalanobis)		K-Mean (Euclidean)	
		Iteration	PSNR	Iteration	PSNR
Canary	6	12	30.943	21	31.052
Parrot	6	18	29.806	25	31.305
Peppers color	6	12	30.210	22	32.931

Table 6 :Shows the quality measures for color images after application EFCMC using Mahalanobis and K-Mean using Euclidean distance .

Image	Clusters	EFCMC (Mahalanobis)		K-Mean (Euclidean)	
		Iteration	PSNR	Iteration	PSNR
Canary	12	26	34.010	56	32.082
Parrot	12	28	33.788	32	31.004
Peppers color	12	28	34.875	44	31.319

1.9 Conclusion

1. The EFCM clustering algorithm improved the result of the hard clustering for an unsupervised classification where Fuzzy clustering methods allow objects to belong to several clusters simultaneously, with different degrees of membership. Any data set is thus partitioned into number fuzzy subsets. The segmented images show more homogenous regions when compared with the hard clustering.
2. The image segmentation is done using C-Means clustering in 3-D RGB space, so it works perfectly fine with all images.
3. The clarity in the segmented image is very good compared to other segmentation techniques.
4. The clarity of the image also depends on the number of clusters used.
5. The results are compared using both algorithms EFCMC using Mahalanobis and K-Mean using Euclidean distance.
6. The results obtained from the proposed algorithm more accurate than the results obtained from traditional methods such as K-Mean. Where the proposed algorithm can extract the information and the features of colored images by adapting the value of precision of the image input to the algorithm
7. As one can see from the above image in the previous page that the image segmented with Mahalanobis distance did come better than Euclidean Distance when the image is segmented with 4 clusters.
8. That has to be true because the Mahalanobis distance considers the variances also.

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