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Modified K - Medoids Algorithm for Image Segmentation

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***Abstract*— K – medoid algorithm is not suitable for large amount of dataset such as color images, because it requires setting each value as a medoid even if its frequency (i.e. number of pixels of same intensity) is very low. As the color image has number of different intensities to set as medoids it needs more time for calculation. The other major drawback of existing algorithm is to find the optimal number of iterations, in our experimental result we show that how number of iterations play an important role to find the best optimal solution. To overcome this disadvantages this paper gives a modified K – Medoids algorithm by using histogram equalization technique. To prove the efficiency of this new algorithm we provide various experimental results over different images with comparison of the existing algorithm.

Keywords— **Colour image segmentation, Histogram equalization, Old K – Medoids clustering algorithm, Modified K – Medoids clustering algorithm.**

I. Introduction

The main goal of image segmentation [1] [2] is domain independent partitioning of an image into a set of disjoint regions. Various clustering techniques [3] are used for image segmentation. In paper [4] [5] authors use K – Medoids clustering technique for image segmentation, the main drawback of K – Medoid clustering is it takes large amount of time for segmentation which is highly dependent on the number of iteration. In this paper we discussed a modified K – Medoids clustering algorithm which reduces the time without compromising the effectiveness of the algorithm.

The paper is organized as follows. In section II, a brief knowledge about histogram equalization technique is provided. In section III, we give the basic strategy of clustering using existing K – medoids algorithm. In section IV, we introduce our new modified algorithm for image segmentation. In section V, the results of our experiment are listed and the conclusion is covered in section VI.

II. Histogram Equalization

The concept of histogram equalization [6] is to spread otherwise cluttered frequencies more evenly over the length of the histogram. Frequencies that lie close together will dramatically be stretched out. These respective areas of the image that first had little fluctuation will appear grainy and rigid, thereby revealing otherwise unseen details.

A histogram equalization algorithm will determine the ideal number of times each frequency should appear in the image and, theoretically, re-plot the histogram appropriately.

The ideal number of pixels per frequency i is the total number of pixels in the image divided by the total number of possible image frequencies N. The algorithm counts the frequencies from 0 to N and shifts as many pixel frequencies into that position as long as this number of pixels is less than or equal to a certain delimiter that increases linearly to the frequency. If a pixel frequency doesn't fit, it is pushed to the right along the horizontal axis until a place is found.

III. Existing K – Medoids Clustering Algorithm

K-Medoids algorithm: The basic strategy of K - Mediods [4] [5] [7] clustering algorithms is to find k clusters in n objects by first arbitrarily finding a representative object (the Medoids) for each cluster. Each remaining object is clustered with the Medoid to which it is the most similar. K-Medoids method uses representative objects as reference points instead of taking the mean value of the objects in each cluster. The algorithm takes the input parameter k, the number of clusters to be partitioned among a set of n objects. A typical K-Medoids algorithm for partitioning based on Medoid or central objects is as follows:

Input:

K: The number of clusters
D: A data set containing n objects

Output:

A set of K clusters that minimizes the sum of the dissimilarities of all the objects to their nearest medoid.

Method: Arbitrarily choose k objects in D as the initial representative objects;

Repeat:

Assign each remaining object to the cluster with the nearest medoid;
Randomly select a non medoid object Orandom;
Compute the total points S of swap point Oj with Orandom
if S < 0 then swap Oj with Orandom to form the new set of k medoid
Until no change;

The algorithm attempts to determine k partitions for n objects. After an initial random selection of k medoids, the algorithm repeatedly tries to make a better choice of medoids.

IV. MODIFIED K – MEDOIDS CLUSTERING ALGORITHM

Improved K – medoids algorithm: To improve the efficiency of the existing K – Medoids algorithm, we use the concept of histogram equalization technique. This technique reduces the number of intensities, which gives less number of centroids to set as medoids. To reduce the number of iterations we allow each intensity to as medoid only ones. Modified K – Medoids clustering algorithm is as follows:

Input:

K: The number of segments
D: An images

Output:

A segmented image that minimizes the sum of the dissimilarities of all the pixels to their nearest medoid.

Method:

Convert image into gray scale;
Equalize histogram;
Store the equalized intensities into an array;
Select randomly K medoids from array;
Remove the selected medoids from array;
Segment image using this medoids;
Calculate the total cost T and store medoids and cost;

Repeat:

Randomly select a non medoid Orandom from array and remove it from array ;
Assign each remaining pixel to the segment with the nearest medoid;
Compute the new total cost Tnew of swap point Oj with Orandom
if Tnew < T then swap Oj with Orandom to form the new set of k medoid
Until array is not empty;

V. EXPERIMENTAL RESULT

The proposed approach is evaluated using different real images. In our experimental result Figure 5.1.1, 5.2.1 and 5.3.1areoriginal images. Each image is segmentized five times with different number of iteration i.e. 50, 100, 150, 200 and 250, using existing K- Medoids clustering algorithm.

Table 5.1 and table 5.2 shows the time required and cost calculated respectively. Figure 5.4 gives the knowledge that the time required for segmentation is highly dependent on the number of iteration, as the number of iteration increases the required time is also increased but figure 5.5 shows that even though the number of iteration increases, the cost or the intercluster similarity is not change drastically.

Figure 5.1.7, 5.2.7 and 5.3.7 are the segmented output images by using our modified K- Medoids clustering algorithm. Table 5.3 and 5.4 shows the difference in time required and cost between existing and modified algorithm.

Fig. 5.1.1 (Original Image)

Fig. 5.1.2 (segmented image with 50 iterations)

Fig. 5.1.3 (segmented image with 100 iterations)

Fig. 5.1.4 (segmented image with 150 iterations)

Fig. 5.1.5 (segmented image with 200 iterations)

Fig. 5.1.6 (segmented image with 250 iterations)

Fig. 5.1.7 (segmented image using new algorithm)

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Fig. 5.1.1 (Original image)

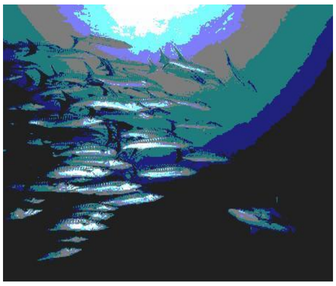

Fig. 5.1.2 (segmented image with 50 iterations)

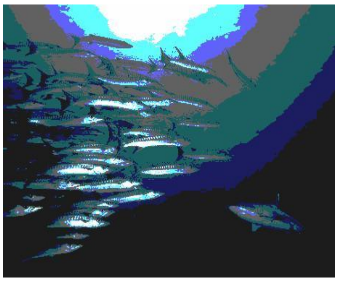

Fig. 5.1.3 (segmented image with 100 iterations)

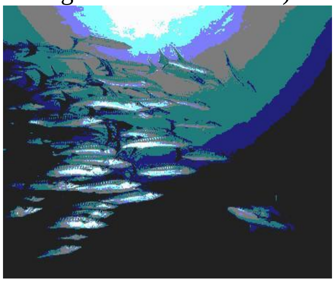

Fig. 5.1.4 (segmented image with 150 iterations)

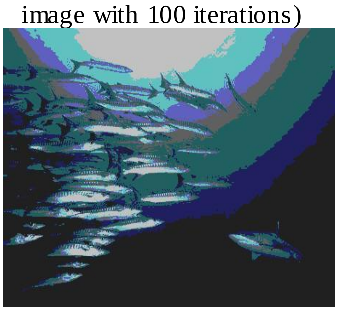

Fig. 5.1.5 (segmented image with 200 iterations)

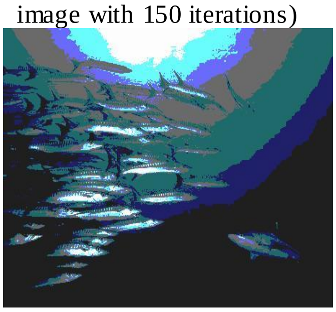

Fig. 5.1.6 (segmented image with 250 iterations)

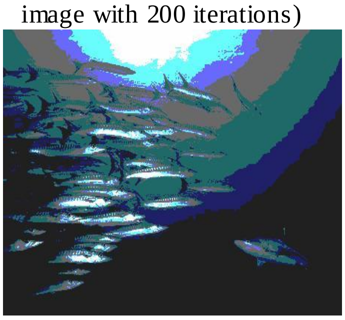

Fig. 5.1.7 (segmented image using new algorithm)

Fig. 5.1.1 (Original image)

Fig. 5.1.2 (segmented image with 50 iterations)

Fig. 5.1.3 (segmented image with 100 iterations)

Fig. 5.1.4 (segmented image with 150 iterations)

Fig. 5.1.5 (segmented image with 200 iterations)

Fig. 5.1.6 (segmented image with 250 iterations)

Fig. 5.1.7 (segmented image using new algorithm)

Table 5.1(Time required for iteration)

TIME (IN SECONDS)			
ITERATION	IMAGES		
	LENA.JPG	TIGER.JPG	SEA.JPG
256	7.08	24.58	13.77
200	6.23	21.92	12.31
150	5.41	19.60	10.93
100	4.69	17.57	9.56
50	3.94	15.01	8.18

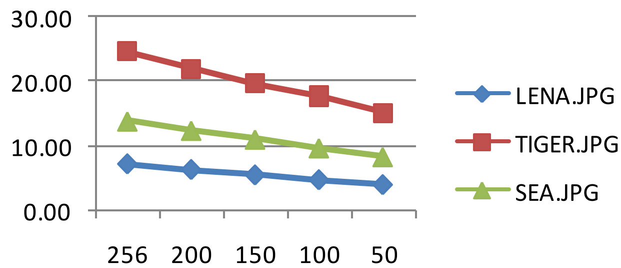

Fig. 5.4 (Graph for Time required for iteration)

Table 5.2 (Cost / Dissimilarity b/w pixels)

COST(DISSIMILARITY B/W PIXELS)			
ITERATION	IMAGES		
	LENA.JPG	TIGER.JPG	SEA.JPG
256	663.45	2420.22	771.16
200	656.02	2447.26	790.70
150	650.26	2474.94	827.31
100	672.74	2434.17	791.38
50	658.77	2448.44	840.49

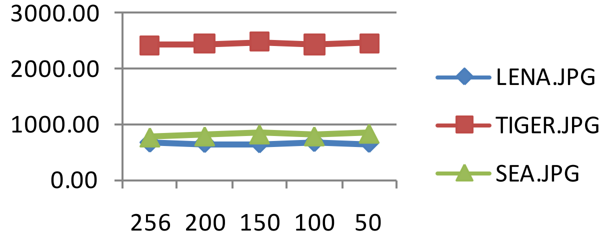

Fig 5.5 (Graph for Cost / Dissimilarity b/w pixels)

Table 5.3 (Difference of time required between Existing and Modified K – Medoids algorithm)

IMAGES	*TIME (SECONDS)*		
	OLD(Avg.)	NEW	DIFF(%)
LENA.JPG	5.47	4.40	24.32
TIGER.JPG	19.74	16.71	18.15
SEA.JPG	10.95	9.10	20.30

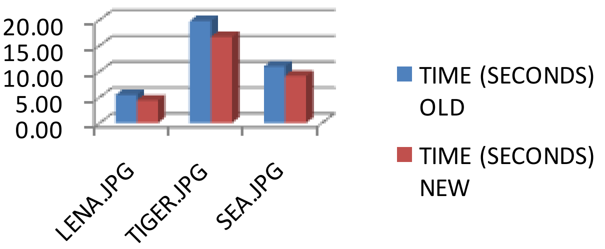

Fig. 5.6(Graph for difference of time required between Existing and Modified K – Medoids algorithm)

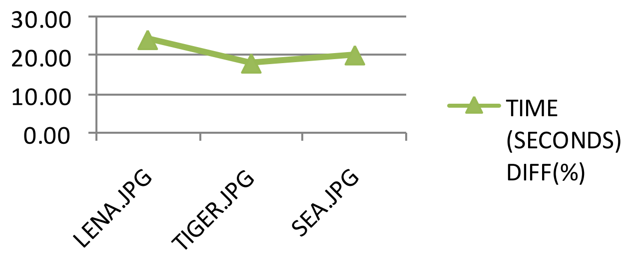

Fig. 5.7 (Time gain in Percentage)

Table 5.4 (Difference of cost between Existing and Modified K – Medoids algorithm)

IMAGES	*COST(DISTANCE)*		
	OLD(Avg.)	NEW	DIFF(%)
LENA.JPG	660.24	664.37	-0.62
TIGER.JPG	2445.01	2439.69	0.22
SEA.JPG	804.21	787.83	2.08

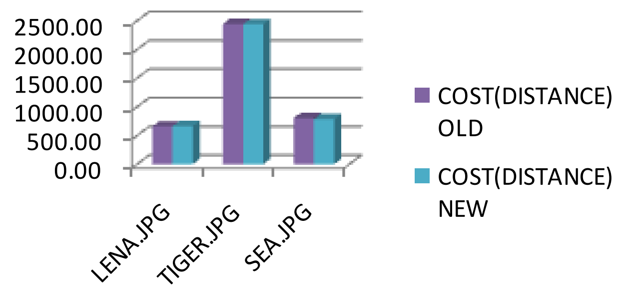

Fig. 5.7 (Difference of cost between Existing and Modified K – Medoids algorithm)

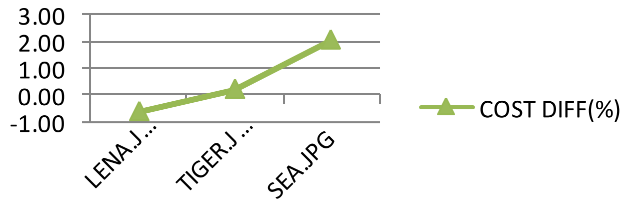

Fig. 5.8 (Deviation in cost calculation in different images)

VI. Conclusion and Future Work

In this paper we suggest an improved K – Medoids clustering algorithm for image segmentation. Various experimental data are discussed in section V. Table 5.3 and table 5.4 shows the comparison between the K – medoids and our modified algorithm. The graph on fig. 5.7 shows that the new algorithm gives better time saving strategy up to nearly 25%. It shows that algorithm is useful for images containing large number of pixels (e.g. Tiger.jpg 642*340).Graph on fig 5.8 shows that the new algorithm work efficiently without affecting a large difference in intercluster similarity, some time it is more than the original algorithm but it is very less (less than 1%). Our future work incorporates the further improvement of the algorithm which reduces the time and increases the intercluser similarity.

VII. References

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