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## Evaluation of Clustering Image Using Steady State Genetic and Hybrid K-Harmonic Clustering Algorithms

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**Abstract-** **T**he goal of clustering is to determine the intrinsic grouping in a set of unlabeled data depending on some similarity measure (e.g. Euclidean distance). In this paper a steady state genetic algorithm (SSGA) approach is used to cluster true color images. After splitting the original images into red, green and blue components and displaying the image of each part, Steady State Genetic Algorithm (SSGA) is used to cluster the image to determine the number of clusters for the image by generating an initial population randomly and then applying the different operations of GA such as fitness function computation, selection, crossover, mutation and stopping condition. In the Crossover stage 1X, PMX and UX methods used for crossover between two parents to produce a new child. In addition to that another clustering method which combines k-mean algorithms and k-harmonic mean algorithms are used. The last clustering algorithm uses two functions to find the cluster centers for each image. Finally root mean square error is used to find the difference between the clustering and original image.

**Keywords** - The steady state genetic algorithm (SSGA), UX method, k-mean.

## 1. Introduction

Clustering can be considered as the most important unsupervised learning problem; so, as every other problem of this kind, it deals with finding a structure in a collection of unlabeled data. A loose definition of clustering could be “the process of organizing objects into groups whose members are similar in some way” [1]. A cluster is therefore a collection of objects which are “similar” between them and are “dissimilar” to the objects belonging to other clusters [2]. The similarity criterion is distance: two or more objects belong to the same cluster if they are “close” according to a given distance. Clustering algorithms may be classified as listed below [3]:

- Exclusive Clustering
- Overlapping Clustering
- Hierarchical Clustering
- Probabilistic Clustering

In the first case data are grouped in an exclusive way, so that if a certain data belongs to a definite cluster then it could not be included in another cluster [4]. On the contrary the second type, the overlapping clustering, uses fuzzy sets to cluster data, so that each point may belong to two or more clusters with different degrees of membership. In this case, data will be associated to an appropriate membership value. Instead, a hierarchical clustering algorithm is based on the union between the two nearest clusters. The beginning condition is realized by setting every data as a cluster. After a few iterations it reaches the final clusters wanted. Finally, the last kind of clustering uses a completely probabilistic approach [5]. An important component of a clustering algorithm is the distance measure between data points. If the components of the data instance vectors are all in the same physical units then it is possible that the simple Euclidean distance metric is sufficient to

successfully group similar data instances [6].

## 2. Related Works

Clustering Image segmentation is a process of dividing an image into different regions based on certain attributes such as intensity, texture, color, etc. This process is fundamental in computer vision and many applications, such as object recognition, image compression, image retrieval, and visual summary, which can benefit from it.

Color images can increase the quality of segmentation, but increase the complexity of problem. Genetic algorithms are well suited to optimizing this complex problem. Pachunde et al., [7] gave a state-of-the-art Genetic Algorithm based clustering methods. Gui et al., [8] applied K-harmonic means instead of K-means to improved spectral clustering procedure in order to raise its stability and performance. Experimental results show that the proposed approach is effective on SAR image segmentation and has the advantage of calculating quickly. Sankari and Chandrasekar [9] used genetic algorithm to find optimal color classes so that the colors in the natural image are clustered sharply. Al-Guwaizani [10] Suggested a Variable Neighborhood Search (VNS) to improve a recent clustering local search called K-Harmonic Means (KHM). Hauschild et al., [11] proposed a hybrid genetic algorithm to perform image segmentation based on applying the q-state Potts spin glass model to a gray scale image. First, the image is converted to a set of weights for a q-state spin glass and then a steady-state genetic algorithm is used to evolve candidate segmented images until a suitable candidate solution is found. Hierarchical local search is used on each evaluated solution in order to speed up the convergence to an adequate solution.

### 3. The genetic algorithms

Most of the classical search methods used to solve the optimization problems suffered from a number of problems and difficulties especially when used to solve a complex problem. Below are some of the problems which the methods suffered from [12].

- 1- The approximate to the optimal solution depended on the selected initial solution.
  - 2- The classical methods are not efficient to treat with the discrete variables.
- All the genetic algorithms in random population, represented as the set of the solution, allocated to each solution specific "fitness" connected directly with the object function for the specific problem and then another population is generated from applying a set of genetic operators like selection, crossover, mutation, continuously and sequential to the generation of that population until the condition is satisfied [13]. Moreover, genetic algorithm characteristically solves most difficulties and problems mentioned above which the classical methods suffered from [14]. Below are the following properties:-

- 1- The genetic algorithms worked on coding the set of parameters which represent the variables of the decision to the problem and not on the parameters itself.
- 2- The genetic searches from a set of point in the search space and not on the one point like the classical methods.
- 3- The genetic algorithm uses the object function information and not derivative or no other information.
- 4- The genetic algorithms used the probabilistic rules and not deterministic rules [15].

There are two basic forms of the genetic algorithms:-

- 1- The simple genetic algorithm (SGA).

- 2- The steady state genetic algorithm (SSGA)

The second of the genetic algorithms have been used in our study, in which the population changes gradually to generate the new generation one after one.

### 4. The Proposed System

Figure 1 shows the block diagram of the proposed system. In the following, the function of each block will be described.

#### 4.1 Read Image

In this stage of the proposed system the images acquired consist of four parts (red, green, blue, additional part). After separating these parts, we need to contract the resulted image and then display images. The read processing of images file depends on image file format.

#### Algorithm:-read image

```

Pos = 54
i = 1
Do
  Get #1, pos, r1 (i): pos = pos + 1
  Get #1, pos, b1 (i): pos = pos + 1
  Get #1, pos, g1 (i): pos = pos + 1
  i = i + 1
Loop Until i >= height * width
x = 1
y = h
i = 1
Do
  R(x, y) = r1 (i): r2(x, y) = r1 (i)
  G(x, y) = g1 (i): g2(x, y) = g1 (i)
  B(x, y) = b1 (i): b2(x, y) = b1 (i)
  x = x + 1
If x > width Then
  x = 1
  y = y - 1
End If
  i = i + 1
Loop Until i > w * h
i = 1
Do
  Get #1, i, a
  Put #2, i, a
  i = i + 1
Loop Until i = 55
Close #1
Close #2

```

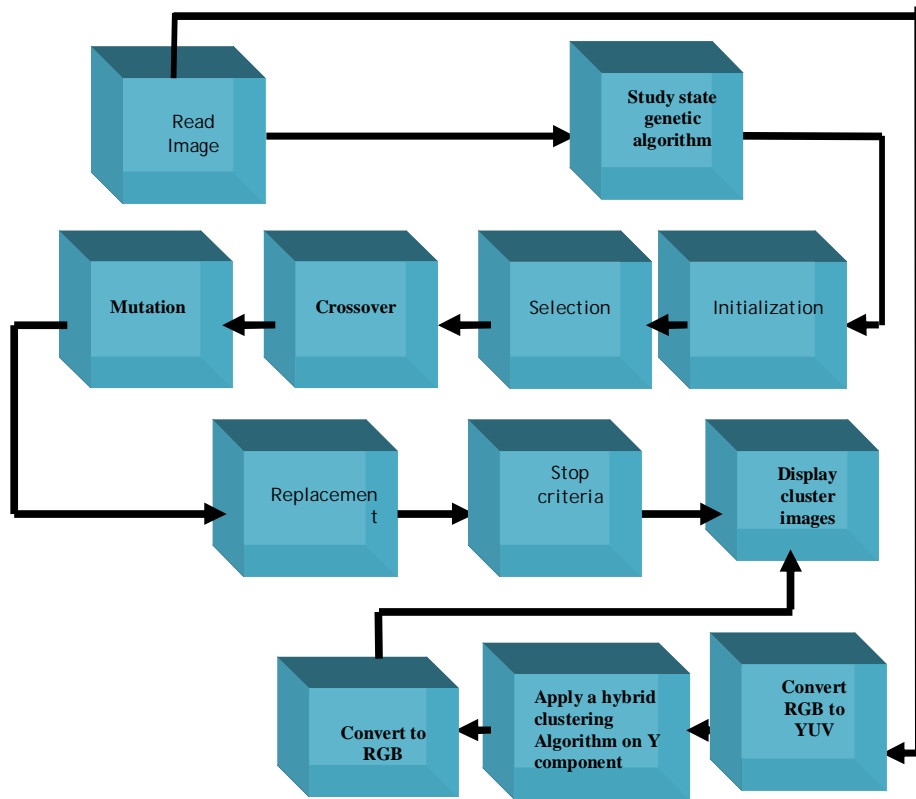


Figure 1: A block diagram of proposed system

**4.2. Study state genetic algorithm**

**4.2.1. Initialization step**

In this stage each chromosome is constructed from

X: taken from the width of the image randomly

Y: taken from the height of the image randomly.

The population consists of a number of chromosomes. Each chromosome contains a number of genes. Each gene consists of (x, y, red, green, blue) where x, y represented the location of the pixels in the image selected randomly.

**Algorithm :-initialization**

```

For i1 = 1 to popsiz
For j1 = 1 to the length of the chromosome
    popu.popul (i1).chromosome mosome (j1).x =
    Int ((w * Rnd) + 1)
    popu.popul (i1).chromosome mosome (j1).y =
    Int ((h * Rnd) + 1)
    
```

```

X1 = popu.popul (i1).chromosome mosome (j1).x
Y1 = popu.popul (i1).chromosome mosome (j1).y
popu.popul (i1).chromosome mosome (j1).red =
r(X1, Y1)
popu.popul (i1).chromosome mosome (j1).grn =
g(X1, Y1)
popu.popul (i1).chromosome mosome (j1).blu =
b(X1, Y1)
    
```

**4.2.2. Evaluation step**

The fitness of a chromosome is computed using the Euclidean distance. If  $p_1(x_1, y_1)$  and  $p_2(x_2, y_2)$ , it is  $\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$ .

**Algorithm Evaluation**

```

For i=1 to pop size
Sum=0
For i11 = 1 to pop size
    Sume = 0
    dist = 0
    fit = 0
For i = 1 to image width
    
```

For  $j = 1$  to image height

$pix.xx = i$

$pix.yy = j$

$pix.rr = r(i, j)$

$pix.gg = g(i, j)$

$pix.bb = b(i, j)$

For  $j11 = 1$  to chromosome length

$Dx = ((pix.xx - popu.popul(i11).chromosome(x)^2) / width$

$Dy = ((pix.yy - popu.popul(i11).chromosome(j11).y)^2) / height$

$Dr = ((pix.rr - popu.popul(i11).chromosome(j11).red)^2) / 256$

$Dg = ((pix.gg - popu.popul(i11).chromosome(j11).grn)^2) / 256$

$Db = ((pix.bb - popu.popul(i11).chromosome(j11).blu)^2) / 256$

$Dst = dx + dy + dr + dg + db$

$ds1 = (dst)^{0.5}$

$Minn(j11) = ds1$

$Mine = minn(1)$

For  $j1 = 1$  to  $chlen$

If  $minn(j1) \leq mine$  Then

$Mine = minn(j1)$

$k = j1$

End If

$Varr(k) = varr(k) + mine$

For  $k1 = 1$  to  $chlen$

$Sume = Sume + varr(k1)$

Next  $k1$

$Dist = Sume / (h * w * 5)$

$Fit = 1 / (1 + dist)$

$fitt(i11) = fit$

For  $i11 = 1$  to  $pop\ size$

$popu.popul(i11).fit = fitt(i11)$

#### 4.2.3. Selection step

The first crossover operator is selected randomly from the population size which represented the first parent and then the second crossover operator is randomly chosen representing the second parent with a condition that any two parents are not to have the same value at each iteration.

#### Algorithm Selection:-

Step1:-Generate first parent ( $r1$ )

Step2:- generate second parent ( $r2$ )

Repeat step (2) until  $r1$  become different from  $r2$

Step3:- if  $fitness(r1) > fitness(r2)$  then

$Per = r1$

Else

$Per = r2$

End if

Step4:- selection  $r1$  or  $r2$  is depending on the fitness function.

Step5:- repeat these steps from (step1) to (step4) to generate the second parent.

#### 4.2.4. Crossover step

Perform crossover step by using (UX). This operator is considered to be very different from others, which has been randomly exchanged with probability (0.5). From the genetics of parents two children are produced. This crossover method has large effective to destroy the chromosome but almost gives a good performance. The power of this method is its ability to enhancement the variety of the population. This method depends on the SSGA.

#### Algorithm Crossover:-

For  $i = 1$  to the length of the chromosome

Generate  $w = Rnd(2)$

If  $w = 1$  Then

$Chld(1).chromosome(i).x = popul$

$(per1).chromosome(i).x$

$Chld(1).chromosome(i).y = popul$

$(per1).chromosome(i).y$

$Chld(1).chromosome(i).red = popul$

$(per1).chromosome(i).red$

$Chld(1).chromosome(i).grn = popul$

$(per1).chromosome(i).grn$

$Chld(1).chromosome(i).blu = popul$

$(per1).chromosome(i).blu$

End If

If  $w = 0$  Then

$Chld(1).chromosome(i).x = popul$

$(per2).chromosome(i).x$

$Chld(1).Chromosome(i).y = popul$

$(per2).chromosome(i).y$

$Chld(1).Chromosome(i).red = popul$

$(per2).chromosome(i).red$

$Chld(1).Chromosome(i).grn = popul$

$(per2).chromosome(i).grn$

$Chld(1).Chromosome(i).blu = popul$

$(per2).chromosome(i).blu$

End If

For  $i = 1$  to the length of the chromosome

Generate  $w1 = Rnd(2)$

If  $w1 = 0$  Then

$Chld(2).Chromosome(i).x = popul$

$(per1).chromosome(i).x$

$Chld(2).Chromosome(i).y = popul$

$(per1).chromosome(i).y$

$Chld(2).Chromosome(i).red = popul$

$(per1).chromosome(i).red$

```

Chld (2).Chromosome (i).grn =popul
(per1).chromosome (i).grn
Chld (2).Chromosome (i).blu = popul
(per1).chromosome (i).blu
End If
If w1 = 1 Then
Chld (2).Chromosome (i).x = popul
(per2).chromosome (i).x
Chld (2).Chromosome (i).y = popul
(per2).chromosome (i).y
Chld (2).Chromosome (i).red = popul
(per2).chromosome (i).red
Chld (2).Chromosome (i).grn = popul
(per2).chromosome (i).grn
Chld (2).Chromosome (i).blu = popul
(per2).chromosome (i).blu
End If

```

#### 4.2.5. Mutation

From the two children generated from the crossover stage a number of genes is randomly chosen not exceeding the length of the chromosome. Then x, y are randomly generated which represent a pixel of the image and exchange the x, y contain at this selected genetic with new generated x,y. then evaluated the new population generated at the same fitness function.

##### Mutation algorithm

```

Generate the first mutation operator ra1randomly
from the chromosome (ran1)
Generate the first mutation operator ra2 randomly
from the chromosome (ran2)
Generate m1genx randomly from the width
Generate m1genyrandomly from the height
Generate m2genx randomly from the width
Generate m2geny randomly from the height
Chld (1).chromosome (ran1).x = m1genx
Chld (1).chromosome (ran1).y = m1geny
Chld (1).chromosome (ran1).red = r (m1genx,
m1geny)
Chld (1).chromosome (ran1).grn = g (m1genx,
m1geny)
Chld (1).chromosome (ran1).blu = b (m1genx,
m1geny)
Chld (2).chromosome (ran2).x = m2genx
Chld (2).chromosome (ran2).y = m2geny
Chld (2).chromosome (ran2).red = r (m2genx,
m2geny)
Chld (2).chromosome (ran2).grn = g (m2genx,
m2geny)
Chld (1).chromosome (ran2).blu = b (m2genx,
m2geny)

```

#### 4.2.6. The replacement

At this study we use Binary Tournament Replacement to replace new people instead of the worst of the two persons chosen randomly. The parameter of choosing the best person depends on the height fitness function.

##### Replacement algorithm

```

If Chld (benu).fit > popu.popu1 (popsiz).fit Then
    popu.popu1 (popsiz) = Chld (benu)
End If
Where benu is the best person result.

```

Also in our work the error function has been used to find the amount error produced through the image clustering.

#### 4.2.7. Stop criteria

To stop all above steps when we found the more fitness function have the similar or approximately value consequently.

### 5. Convert RGB to YUV color space

There are many slightly different formats to convert between YUV and RGB. These formulas assume U and V are unsigned bytes [16] [17].

$$Y=R*0.299000+G*0.587000+B*0.114000$$

(1)

$$U=R*-0.168736+G*-0.331264+B*0.500000+128$$

(2)

$$V=R*0.500000+G*-0.4188+B*-0.081312+128$$

(3)

### 6. The algorithm of the hybrid clustering Algorithm

1. Begin
2. Initialize Dataset DN, K, C<sub>1</sub>, C<sub>2</sub>, . . . , C<sub>K</sub>, Current Pass=1; where D is dataset, N is size of data set, K is number of clusters to be formed, C<sub>1</sub>, C<sub>2</sub>, . . . , C<sub>K</sub> are cluster centers. Current Pass is the total no. of scans over the dataset.

3. Do assign the n data points to the closest  $C_i$ ;
- If Current Pass%2==0
- Recomputed  $C_1, C_2, \dots, C_K$  using Harmonic Mean function;
- Else
- Recomputed  $C_1, C_2, \dots, C_K$  using Arithmetic Mean function;
- Increase Current Pass by one.
- Until no change in  $C_1, C_2, \dots, C_K$ ;
4. Return  $C_1, C_2, \dots, C_K$ ;
5. End

**7. Case study**

This system is tested for different types of images. Some of these cases can be shown below in Tables 1 and 2 and Tables 3 and 4.

Case 1: Test the system on the flower image in Table (1), multi objective image based on SSGA clustering algorithm in Table 2 as shown in Figures 1 and 3.

**Table (1): The tested system on the flower image using SSGA**

<b>Image size</b>	<b>128*128</b>
<b>No. of population</b>	<b>20</b>
<b>Chrom.length</b>	<b>10</b>
<b>Max fitness</b>	<b>0.6892686</b>
<b>Error value</b>	<b>0.868438837140105</b>



Enter chrom length	Enter pop. size	Enter the picture name	image data	
20	10	FLWR0706.bmp		Note:- Please enter picture name in the first text box th click on "enter picture name command", then you must click on command"Store in array to store the value of pixels in the picture after that please enter pop size in the second text box then enter the chrom length or the no. of Gens in the chromosom , then click on the command "Clustering operation "" and wait several minite to see the result.
store in array is finish	the production image	original image	73 33 3	
enter picture name			56 67 6	
store in array			148 77 4	
clustering operation			189 76 2	
exit			167 39 6	
red			158 52 4	
			197 51 2	
			165 44 7	
			153 61 10	
			170 59 2	
			143 62 14	
			98 81 20	
			177 78 3	
			142 35 17	
			106 63 24	
			153 49 6	
			133 17 9	
			40 41 15	
			85 27 1	
			72 31 3	
			38 52 3	
			100 40	
			84 41 3	
			38 74 4	

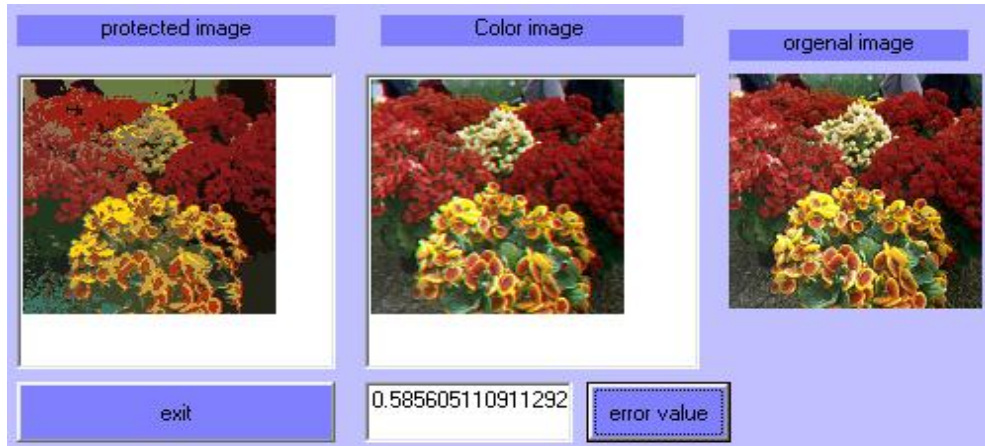
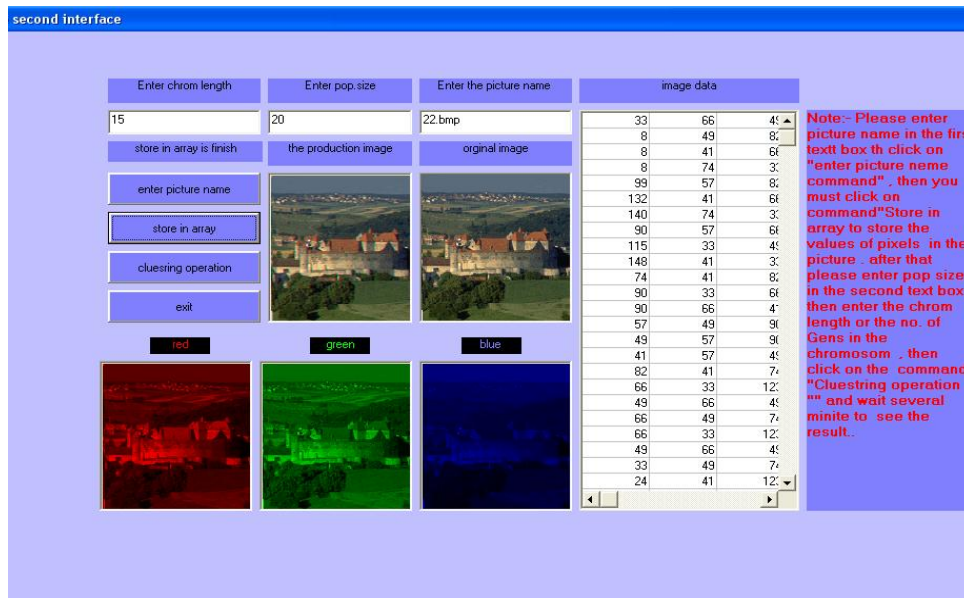


Figure (2): the implementation of the SSGA on flower image

Table (2): The tested system on the multi objective image using SSGA

<b>Image size</b>	<b>160*160</b>
<b>No.of population</b>	<b>20</b>
<b>Chrom.length</b>	<b>15</b>
<b>Max fitness</b>	<b>0.6295041</b>
<b>Error value</b>	<b>0.292862378706691</b>





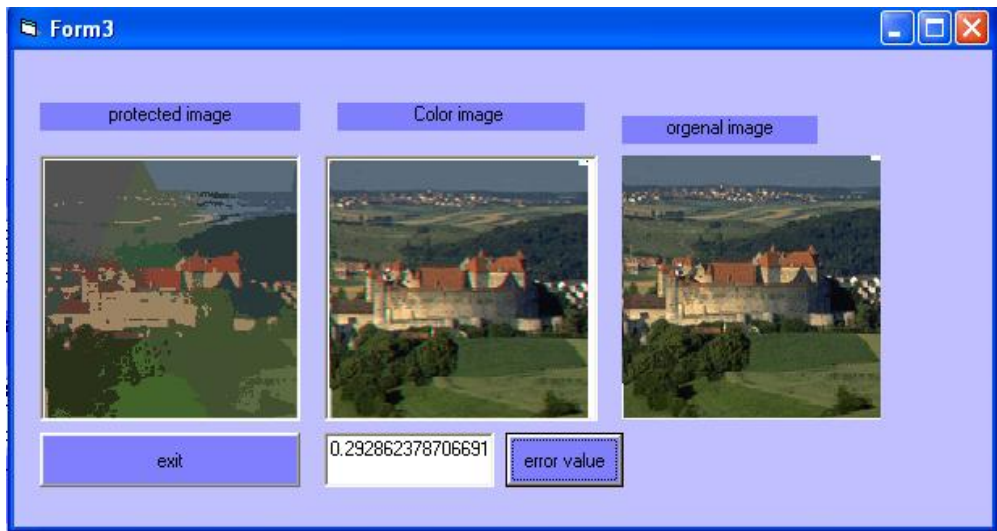


Figure (3): the implementation of the SSGA on multi object image

Case 2: flower image and multi object image tested on the hybrid clustering method

Table (3): The tested system on the flower image using hybrid k-harmonic algorithm



Image size	128*128
No. of iteration	30
Number of cluster	10
Error value	1.41576730294866E-05

Table (4): The tested system on the multi objective image using hybrid k-harmonic algorithm

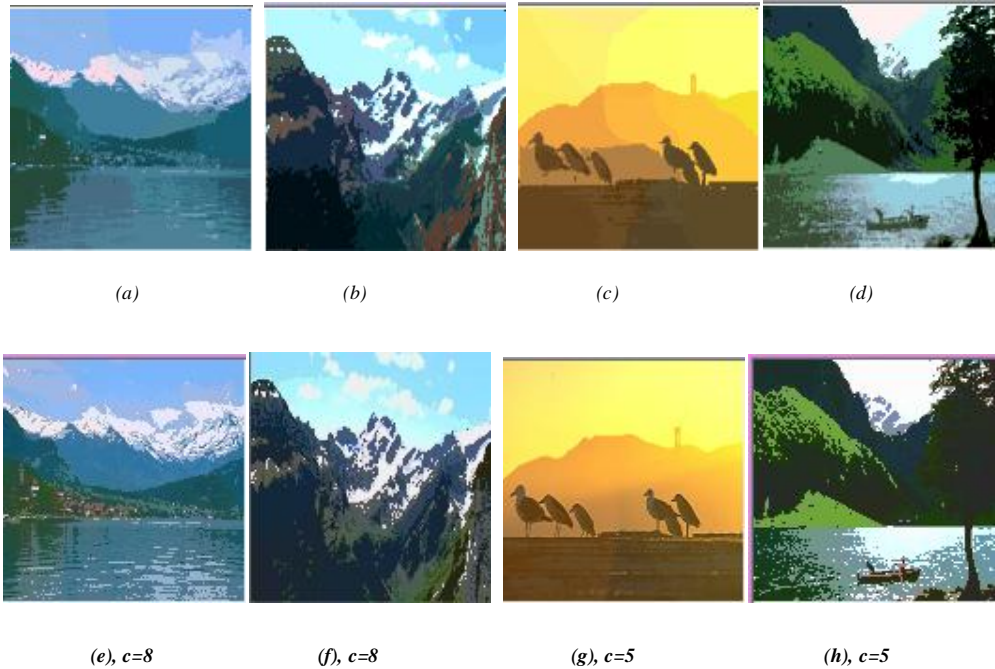


Image size	128*128
No. of iteration	30
Number of cluster	10
Error value	1.41576730294866E-05

Figure (4): the implementation of hybrid clustering algorithm on the above image

Also, this system is tested on different true images and the behavior for these clustering methods can be shown in figure (5). Figures a, b, c and d show the

behavior of the SSGA, whereas e, f, g and h show the behavior of the hybrid algorithm.



**Figure (5): The implementation for the proposed system for both methods for different cluster numbers**

## 8. Conclusion

- a- The relation between the distance and the fitness function is reversed. This means (I.e.  $\text{fitness} = 1/\text{distance}$ ).
- b- The number of the clusters depends on the image's nature and complexity and not on the size of the image.
- c- The resulted cluster images depend on the nature and complexity of the image.
- d- The increasing of the size of the population and the length of the chromosome obtained the best resulted in the SSGA algorithm.
- e- The error value of the homogeneous color image is greater than non-homogenous color image although the clustering process in the homogenous is better.
- f- The three methods of crossover (1X, UX, PMX) which have been used in this paper have the same result; this refers to the power of the fitness function.
- g- The hybrid k-harmonic clustering method provided suitable results in a less number of iterations; also the root mean square error is small which reflects the goodness of this method.
- h- The result presented in this paper showed that the hybrid k-harmonic clustering method is more suitable than the other methods, which gave a good result in small number of clustering.
- i- Using of RGB color space in the first method and converting RGB to YUV color space in the second method provide good results.

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