Color quantization with clustering by F-PSO-GA

Article · October 2010

DOI: 10.1109/ICICISYS.2010.5658548

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***Abstract*—Color quantization is a technique for processing and reduction colors in image. The purposes of color quantization are displaying images on limited hardware, reduction use of storage media and accelerating image sending time. In this paper a hybrid algorithm of GA and Particle Swarm Optimization algorithms with FCM algorithm is proposed. Finally, some of color quantization algorithms are reviewed and compared with proposed algorithm. The results demonstrate Superior performance of proposed algorithm in comparison with other color quantization algorithms.**

Keywords-Clustering; Color quantization; FCM algorithm; Genetic algorithm; Particle Swarm Optimization(PSO)algorithm;

I. INTRODUCTION

Color quantization is a common image processing technique that allows the representation of true color images using only a small number of colors [1]. True color images typically use 24 bits per pixel which results in an overall gamut of 2^{24} i.e. more than 16 million different colors. Color quantization uses a color palette that contains only a small number of colors (usually between 8 and 256). Clearly the choice of the colors that make up the palette has a crucial influence on the image quality of the quantized image. However, the selection of the optimal color palette is known to be an np-hard problem [2]. Color quantization is useful for displaying images on limited hardware such as mobile devices, for image compression, and for other applications such as image retrieval [1,3]. In fact, main purposes of color quantization are reduction use of storage media and accelerating image sending time [4].

Color quantization can be performed by image clustering. Color quantization methods with clustering include two essential phases. In the first phase, specific numbers of colors (K colors) are extracted from image for making a palette. In the second phase, every pixel of images is replaced by one of these colors [5].

In the image processing literature many different algorithms have been introduced that aim to find a palette that allows for good image quality of the quantized image [1,2,6,7]. One of the most important and simplest using algorithms is K-Means algorithm. This algorithm subdivides data to k clusters by use of Euclidean data distance criterion. This algorithm is sensitive to primary center selection conditions and may get involved in the local optimums and doesn't obtain the best clusters' position [5].

Fuzzy c-means (FCM) is based on the idea of finding cluster centers by iteratively adjusting their positions and evaluation of an objective function similar to c-means, yet it allows more flexibility by introducing the possibility of partial memberships to clusters [1]. Soft computing techniques such as genetic algorithms have also been employed to extract a suitable palette [1,8,9].

Particle swarm optimization algorithm is one of heuristic search approach proposed by Kennedy and Eberhart in 1995[10]. PSO is an evolutionary optimization algorithm based on swarm that is simulated in the imitation of the social and flocking behavior of birds. This approach like most of evolutionary search algorithm starts search in parallel with a population (swarm). Then it appoints fitness of every individuals of population based on a cost function and updates the information of population by use of fitness values. This procedure repeats until convergence [5]. Some applications of PSO are as follows: Data clustering [11], Feature selection [12], Artificial Neural Network [13,14,15], routing [13,16], solving the traveling salesman problem [13]. In [5], the combination of PSO and K-Means is used for color quantization. Artificial Neural Networks are used to find a color image palette, too [4,17,18].

In this paper, hybrid of PSO, GA and FCM algorithm is used for image pixel clustering, which has merits of these three algorithms. In continuation, PSO algorithm is reviewed in section 2 and in section 3 the hybrid algorithm of PSO and GA is discussed. In section 4, FCM algorithm is expressed. In section 5 the proposed algorithm F-PSO-GA is described. Section 6 presents the experiments and results.

I. PARTICLE SWARM OPTIMIZATION ALGORITHM

In PSO algorithm, the solution of each problem is a bird in the search space called particle. Every particle has a fitness value which is obtaining by fitness function. The bird which is closer to food has more fitness value. PSO starts with a group of random answers (particles), then it searches for finding optimal answer in problem space by updating particle positions.

Every multi dimensional particle (depending on the problem nature) is specified by X_{id} and V_{id} which denote the location position and speed of dimension d^{th} of particle i. In every phase of swarm movement, position of each particle is updated by two best values. The first value is the best answer according to fitness which is obtained for each particle separately until now and is called p_best. Another value is the best value that is obtained by all of particles through total swarms until now and is called g_best. If a neighborhood is defined for every particle, this value is computed in this neighborhood. In this case, this value is called l_best. In every iteration of the algorithm, the new speed and position of each particle are updated by (1) and (2), after finding p_best and g_best (or l_best) [10]:

$$
\begin{aligned}
v_{id}(t+1) = {} & w.v_{id}(t) \\
& + c_1.rand(p\_best_{id} - x_{id}) \qquad (1) \\
& + c_2.rand(g\_best_d - x_{id})
\end{aligned}
$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1), \qquad (2)$$

where in (1), w is an inertia weight in interval [0,1], c_1 and c_2 are learning coefficients or acceleration in interval [1,2] (usually $c_1 = c_2$) and $rand$ is a random number in interval [0,1]. Also final value of every particle's speed is limited to a maximum value for avoiding divergence $v_{id} \in [-v_{\max}, v_{\max}]$. Algorithm stopping criterion is convergence of it or after specific numbers of iterations [5].

II. HYBRID PSO AND GA

The drawback of PSO is that the swarm may prematurely converge. A further drawback is that stochastic approaches have problem-dependent performance. This dependency usually results from the parameter settings in each algorithm. In general, no single parameter setting can be applied to all problems. Increasing the inertia weight (w) will increase the speed of the particles resulting in more exploration (global search) and less exploitation (local search). Thus finding the best value for the parameter is not an easy task and it may differ from one problem to another. Therefore, from the above, it can be concluded that the PSO performance is problem-dependent. The problem-dependent performance can be addressed through hybrid mechanism. It combines different approaches to be benefited from the advantages of each approach. To overcome the limitations of PSO, hybrid algorithms with GA are proposed. The basis behind this is that such a hybrid approach is expected to have merits of PSO with those of GA. One advantage of PSO over GA is its algorithmic simplicity [19]. This simplicity will result in the increase of speed calculations and the reaching to the desired answer with low volume of memory [5]. Another clear difference between PSO and GA is the ability to control convergence. Crossover and mutation rates can subtly affect the convergence of GA, but these cannot be analogous to the level of control achieved through manipulating of the inertia weight. In fact, the decrease of inertia weight dramatically increases the swarm's convergence. The main problem with PSO is that it prematurely converges to stable point, which is not necessarily maximum. To prevent the occurrence, position update of the global best particles is changed. The position update is done through some hybrid mechanism of GA. By applying crossover operation, information can be swapped between two particles to have the ability to fly to the new search area. The purpose of applying mutation to PSO is to increase the diversity of the population and the ability to have the PSO to avoid the local maxima.

There are three different hybrid approaches are proposed in [19]. The first and second approach only uses crossover and mutation with PSO algorithm respectively. In the third approach, GA and PSO algorithms run individually. In this model the total numbers of iterations are equally shared by GA and PSO. First half of the iterations are run by GA and the solutions are given as initial population of PSO. Remaining iterations are run by PSO.

III. FCM ALGORITHM

Ruspini proposed the first fuzzy clustering model in 1969 [20]. In this approach, the membership of each data point to every cluster is denoted by membership matrix $U = [u_{ij}]_{c\times n} = (\vec{u}_1, \vec{u}_2, ..., \vec{u}_n)$, where c is the number of clusters and n is the number of data points. In this approach, there are two main restrictions. First, none of clusters is empty $(\sum_{j=1}^{u} u_{ij} > 0 \quad \forall i \in \{1,...,c\})$. The second restriction called normalizing restriction expresses that sum of every data point's membership to all of clusters must be 1 $(\sum_{j=1}^{c} u_{ij} = 1 \quad \forall j \in \{1,...,n\})$. FCM algorithm tries to find for a collection of data points so partitions (c fuzzy clusters) which minimum the following cost or target function:

$$J_f(X, U_f, C) = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^m d_{ij}^2, \qquad (3)$$

where d_{ij} is the distance between data X_j and the cluster center i and $m \in [1,\infty)$ defines fuzziness.

But J_f function cannot be minimized directly; therefore we should use iterative algorithms. For solving this problem, alternating optimization schema is used as follows:

1. Selecting appropriate values for m , c and small positive number for ε . Matrix C (clusters' centers) is initialized randomly. Finally, $t = 0$ is set.

2. Membership matrix is calculated (in $t=0$) or updated (in $t>0$), i.e. membership values are optimized for constant parameters of clusters as follows:

$$u_{ij}^{(t+1)}=\frac{d_{ij}^{-2/(m-1)}}{\sum_{l=1}^{c}d_{lj}^{-2/(m-1)}}=\frac{1}{\sum_{l=1}^{c}(d_{lj}/d_{ij})^{1/(1-m)}} \quad (4)$$
$$for \quad i=1,...,c \quad and \quad j=1,...,N$$

3. cluster prototype matrix is updated according to updated membership values:

$$c_i^{(t+1)}=\frac{\sum_{j=1}^{n}(u_{ij}^{(t+1)})^m\vec{x}_j}{\sum_{j=1}^{n}(u_{ij}^{(t+1)})^m} \quad (5)$$
$$for i=1,...,c$$

4. Repeating 2 and 3 until $\|C^{(t+1)}-C^{(t)}\|<\varepsilon$ or $\|U^{(t+1)}-U^{(t)}\|<\varepsilon$ is correct.

More details of this algorithm are available in [20, 21].

IV. PROPOSED ALGORITHM F-PSO-GA FOR COLOR QUANTIZATION

According to our done experiments and observations, results of hybrid PSO-GA of type 3 in combination with FCM algorithm are visually better in comparison with two other types and have less errors, too. So, the proposed algorithm is expressed according to this basis and done comparisons and results are based on hybrid type 3.

In the proposed algorithm, hybrid PSO-GA is used for finding values of optimum clusters' centers $c_1,c_2,...,c_k$. To this purpose, clusters' centers that (3) is minima for them are assumed as optimum clusters' centers. The first step is defining chromosomes. Since our data is images that each pixel of them has 3 values R, G, B and number of cluster is K –defined by user- so every chromosome has $K\times3$ entries. This structure is as follows:

$$[c_{1,R},c_{1,G},c_{1,B},c_{2,R},c_{2,G},c_{2,B},...,c_{k,R},c_{k,G},c_{k,B}] \quad (6)$$

And (3) is used as fitness function. In continuation, we explain proposed algorithm steps.

Step 1: The population is initialized randomly. To this purpose for every chromosome, K values of image pixel values are selected randomly as initial centers of clusters.

Step 2: for every pixel of the input image, membership value is measured according to (4). Then, for every chromosome, fitness value is calculated from (3). Afterwards centers of clusters are updated by (5). If GA algorithm stopping criterion is not met, step 3a is iterated; otherwise step 3b is done.

Step 3a: GA runs by applying crossover and mutation operations on the population. This algorithm is repeated with given iterations and after checking stopping criterion, goes to step 2. After these specific iterations, the solutions are given as initial population of PSO. Remaining iterations are run by PSO.

Step 3b: p_best and g_best values are updated and centers' values of clusters are transferred to particle positions. Speeds and new positions of particles are computed by use of (1) and (2) respectively. The stopping criterion is checked, if this criterion isn't met, this algorithm goes to step 2 and iterates from step 3b.

V. EXPERIMENTS AND RESULTS

Before explanations of done experiments, it's necessary to introduce criteria for comparing algorithms and then, those algorithms that the F-PSO-GA algorithm is compared to, are explained in summary.

A. *comparison criteria*

Mean Squared Error (MSE) is one of the most important criteria for comparison of two clustering algorithm. For every image with dimensions of $m\times n$, MSE calculated as[1]:

$$MSE(I_1,I_2)=\frac{1}{3nm}\sum_{i=1}^{n}\sum_{j=1}^{m}[(R_1(i,j)-R_2(i,j))^2+(G_1(i,j)-G_2(i,j))^2+(B_1(i,j)-B_2(i,j))^2] \quad (7)$$

where I_1 is original image and I_2 is quantized image and $R(i,j)$, $G(i,j)$ and $B(i,j)$ are the red, green and blue pixel values at location (i,j). Root Mean Squared Error (RMSE) is another criterion that is the root of MSE but in some of papers the division to 3 is not considered [5], so for this reason, the result is multiplied by $\sqrt{3}$ for comparison.

Another criterion to be used is Peak Signal-to-Noise-Ratio (PSNR). PSNR described as [1]:

$$PSNR(I_1,I_2)=10\log_{10}\frac{225^2}{MSE(I_1,I_2)} \quad (8)$$

B. *Introduction of compared algorithms with F-PSO-GA algorithm*

Short description of algorithms that F-PSO-GA algorithm is compared to, are expressed as follows:

K-Means: In this algorithm, data is subdivided to k clusters by use of Euclidean data distance criteria. Every data point belongs to the nearest cluster to it. New centers calculate by averaging the data points in every cluster and this procedure is repeated until convergence [5].

Popularity algorithm [2]: First a uniform quantization step is applied where each color channel is reduced to a bit depth of 5 bits. Then, simply those *n* colors that are represented most often form the color palette [1].

Median cut quantization [2]: This algorithm starts by computing the box that encompasses all colors present in the image. The box is then split (orthogonal to the color axis) at the median value into two sub-cubes. The larger remaining sub-cube is then again divided at its median point and this process is repeated until *n* color boxes have been found [1].

Octree quantization [3]: The color space is represented as an octree where the root node corresponds to the whole color space; the nodes at the next level the eight subcubes that are obtained by dividing each color axis into two equal halves, and so on. In a first pass the sub-tree that represents the colors present in the image is built and in a second pass, starting at the bottom of the tree, nodes are successively merged until a tree of *n* colors is reached [1].

Neuquant [22]: A one-dimensional self-organising Kohonen neural network is trained to generate the color map. The Kohonen network defines a mapping from the color values in the image to an index representing the palette entries. The weights of the network are updated based on the image data to ensure an optimal palette with good image quality [1].

RSFCM [23]: To combat the computational complexity of FCM, This multistage random sampling strategy proposed. This method has a lower number of feature vectors and also needs less iteration to converge [1].

EnFCM [24]: This approach is an alternative to the classical FCM by adding a term that enables the labeling of a pixel to be associated with its neighborhood. As a regulator, the neighborhood term can change the solution towards piecewise homogeneous labeling [1].

AMSFCM [25]: This approach (Anisotropic mean shift based FCM) utilizes an anisotropic mean shift algorithm coupled with fuzzy clustering [1].

SOM [17]: Self-Organizing Map network is used for obtaining color image palette. Artificial network clusters data automatically by feeding with proper sequence of entrance data [4].

FS-SOM [18]: This competitive approach (Frequency Sensitive Self-Organizing Map) uses adapting the Self-Organizing Map network's neighborhood with frequency sensitive learning model and so increments winning ability of neurons which compete less. Learning rate of FS-SOM is proportionate to the number of times that the neurons win [4].

TASOM with butterfly time [4]: This algorithm uses learning rate function and neighborhood function of Time Adaptive Self-Organizing Map network (TASOM) [26] and global butterfly jumping sequence of FS-SOM algorithm. Competitive learning TASOM approach utilizes learning rate and separate neighborhood function for every neuron. With having separate neighborhood radius, it is possible to have more control on the behavior of each neuron independent of other neurons. In this approach, entrance data are applied to network with butterfly jumping sequence like FS-SOM algorithm and learning rate is reduced by time.

C. *Experimental results*

In proposed algorithm implementation, the number of population is 10, c_1 and c_2 parameters are $c_1 = c_2 = 1.5$ and w parameter is decreasing from 0.9 to 0.2 linearly. The numbers of iterations of this algorithm is 50 that the iterations of GA and PSO algorithms are 10 and 40 respectively. We ran the algorithm for girl image with 60 and 100 clusters. Fig. 1 shows original image and resulted image with 60 clusters by proposed algorithm and hybrid PSO and K-Means algorithm. The resulted images' errors are summarized in table 1 in comparison to hybrid PSO and K-Means algorithm. Fig. 1(b) specifies that proposed algorithm result is very better than that of hybrid PSO and K-Means visually and RMSE errors are far less, too (see table 1). Some other results are given in table 2, the first eight rows' results have come from [1] and rows 9 to 11 are from [4] and our algorithm results are in last row. So, these results are compared by PSNR. Table 2 shows F-PSO-GA algorithm results are better; the first best two results in every column are Bold. Some of color quantization results of images are depicted in Fig. 2 and Fig. 3.

Results in tables are the average of 10 runs of our algorithm on the same image with the same k.

TABEL I. Comparison of algorithms by RMSE for Girl image with k=60,100

Algorithms	**K**	**RMSE**
K-Means	60	17.6
	100	14.4
Hybrid PSO and K-Means	60	17.1
	100	14.1
Proposed algorithm (F-PSO-GA)	60	7.0831
	100	6.2528

TABEL II. Comparison of algorithms by PSNR for Lena and Peppers and Baboon images with k=16

	Algorithms	**Lena**	**Peppers**	**Baboon**
1	Popularity	22.24	18.56	18.00
2	Median cut	23.79	24.10	21.52
3	Octree	27.45	25.80	24.21
4	Netuquant	27.82	26.04	24.59
5	FCM	28.81	26.77	**25.03**
6	RSFCM	28.70	26.70	24.98
7	EnFCM	28.61	26.74	24.87
8	AMSFCM	28.63	2671	24.66
9	SOM	29.61	26.70	24.85
10	FS-SOM	29.67	26.70	24.89
11	TASOM With butterfly time	**29.68**	**26.93**	24.90
12	Proposed algorithm	**32.1778**	**28.5582**	**27.0433**

VI. CONCLUSION

One of the most common approaches for color quantization is the use of clustering algorithms in pixel area. There are many algorithms for clustering, some of which were used for color quantization. In this paper a clustering algorithm was represented, which is hybrid of GA and Particle Swarm Optimization algorithms with FCM algorithm. This algorithm was compared to some of color quantization algorithms. The results demonstrate the superiority of the proposed algorithm.

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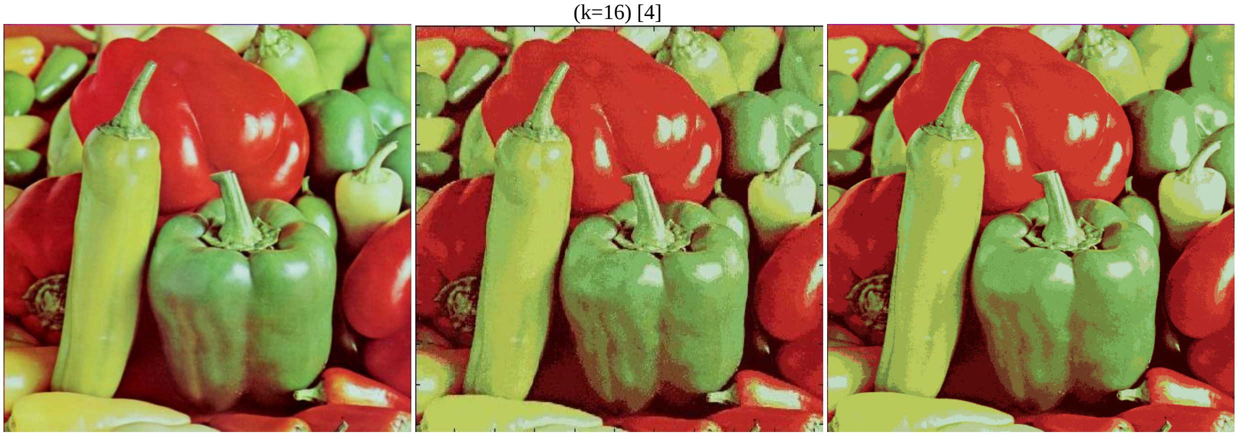
(a) (b) (c)

Figure 1. (a) Girl original images (256*256) (b) quantised image with F-PSO-GA algorithm (k=60) (c) quantised image with hybrid PSO and K-Means algorithm (k=60) [5]

(a) (b) (c)

Figure 2. (a) Lena original images (512*512) (b) quantised image with F-PSO-GA algorithm (k=16) (c) quantised image with TASOM algorithm with butterfly time (k=16) [4]



(a) (b) (c)

Figure 3. (a) Peppers original images (512*512) (b) quantised image with F-PSO-GA algorithm (k=16) (c) quantised image with TASOM algorithm with butterfly time (k=16) [4]