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Color Image Quantization: A Short Review and an Application with Artificial Bee Colony Algorithm

Celal OZTURK*, Emrah HANCER, Dervis KARABOGA

Department of Computer Engineering, Erciyes University, Kayseri, 38039, Turkey
e-mail: celal@erciyes.edu.tr, emrahhancer@erciyes.edu.tr, karaboga@erciyes.edu.tr

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Abstract. Color quantization is the process of reducing the number of colors in a digital image. The main objective of quantization process is that significant information should be preserved while reducing the color of an image. In other words, quantization process shouldn't cause significant information loss in the image. In this paper, a short review of color quantization is presented and a new color quantization method based on artificial bee colony algorithm (ABC) is proposed. The performance of the proposed method is evaluated by comparing it with the performance of the most widely used quantization methods such as K-means, Fuzzy C Means (FCM), minimum variance and particle swarm optimization (PSO). The obtained results indicate that the proposed method is superior to the others.

Key words: color quantization, artificial bee colony, particle swarm optimization, K-means, fuzzy C means.

1. Introduction

It is known that high quality images can be displayed and stored without much effort with the rapid development of computer software and hardware. However, these images can contain a huge amount of detailed information causing transfer time and processing problems. In order to avoid these problems, unnecessary information should be eliminated from images with some pre-processing methods before processing and transmission. For instance, topographic maps needs to be eliminated from the unnecessary color information so as to accurately construct digital evaluation models (DEM) (Samet and Hancer, 2012). Color quantization, accepted as a pre-processing application, is used to reduce the number of colors in images with minimum distortion such that the reproduced image should be very close to the original image visually. In general, color quantization is performed in two steps. The first step is pallete design i.e. selecting appropriate number of colors (generally 8-256). The second step is pixel mapping i.e. replacing each pixel color with the color in the pallete. Therefore, color quantization can be accepted as a lossy image compression operation.

*Corresponding author.

Color quantization plays a critical role in many applications such as segmentation, compression, color texture analysis, watermarking, text localization/detection, non-photorealistic rendering and content-based retrieval (Celebi *et al.*, 2011). It is not possible to obtain the best optimal solution since a color quantization method needs to consider several situations such as minimum difference, method complexity, and the characteristics of human vision system (HVS) (Bing *et al.*, 2004). In other words, it is not possible to preserve the color layers and certain significant details at the same time. For instance, it can be easily seen that essential details representing with a small number of pixels can be lost when the pallete is constructed according to the color layer representing with a great number of pixels in an image. Furthermore, the color layers representing with a great number of pixels can be damaged if the pallete is chosen according to the color layer representing with a small number of pixels i.e. essential details.It can be inferred that obtaining global optimal solution is not feasible since it requires a huge amount of time. Therefore, color quantization is known as NP-complete.

In this paper, a detailed literature review of color quantization methods is given and a new quantization approach based on the artificial bee colony (ABC) algorithm is proposed. The ABC algorithm, proposed by Karaboga (2005), is the simulation of the foraging behaviour of honey bees and has been successfully applied to the various problems by authors such as the optimization of numerical problems (Karaboga and Basturk, 2008), data clustering (Karaboga and Ozturk, 2011), neural networks training for pattern recognition (Karaboga and Ozturk, 2009), wireless sensor network deployment (Ozturk *et al.*, 2011), routing (Karaboga *et al.*, 2012b), and image analysis (Hancer *et al.*, 2012; Ma *et al.*, 2011). The detailed survey of ABC algorithm and its applications can be found in Karaboga *et al.* (2012a). The main motivation of this paper is twofold: (1) to apply ABC algorithm on color quantization problem and (2) to present a survey of recent color quantization methods. It should be mentioned that ABC algorithm has not yet been applied to color image quantization problem and surveys of color quantization methods are not common.

The paper is organized in five sections: Section 2 presents the related works; Section 3 describes an overview of the ABC algorithm; Section 4 presents ABC-based quantization method; and Section 5 summarizes and explains the results and comparisons of the algorithms. Finally, Section 6 concludes the paper.

2. Related Works

Several color quantization methods have been proposed in the literature and these can be categorized into two groups: splitting and clustering-based methods.

2.1. *The Splitting Methods*

The splitting methods divide color spaces into disjoint regions according to some criteria. This process is repeated until getting the desired number of regions. After that, each region is chosen to be the pallete color. Therefore, the set of clusters is constructed by a complete binary tree where each parent has two children (Braquelaire and Brun, 1997). The time consumption of the splitting methods is satisfactory in general. However, it is difficult to find an optimal solution through the splitting decisions.

Uniform quantization (Heckbert, 1982a) considers each axis of color space independently. Each axis is divided into equal sized subspaces. The planes perpendicular to the axis' that pass through the division points then define regions in the color space. The number of these regions is dependent on the scheme used for dividing the color space. One possible scheme is to divide the red and green axis into 8 segments and the blue axis into 4 resulting in 256 regions (Hill, 1990). Although this method is fast and simple, the distortion between the original and reproduced image is generally excessive since the pallete colors do not have any relation with the original image i.e. an image does not include all uniformly distributed colors.

Contrary to the uniform quantization, the median cut method (Kruger, 1994), accepted as the most widely used splitting method, divides color space according to the distribution of original image colors. Firstly, the smallest box comprising all the colors in the image is founded. Then, the closest colors are sorted along the longest axis of the box. Lastly, the box is splitted into two regions at center of the sorted list. The process is repeated until the original color space is divided into 256 colors. The average colors of each box represent palette colors. The colors with high pixel numbers in the same box can be represented well in the reproduced image. In contrast, the colors with low pixel numbers in the same box cannot be represented well in the reproduced image. Thus, the median cut method can keep color layers (the colors with different illumination intensities) very well, but it cannot keep some essential information (Bing *et al.*, 2004). The center cut method (Heckbert, 1982b), similar to the median cut method, divides the color space into the boxes which have the longest side until obtaining the predefined number of colors. The positions after the division process are close to the colors with more pixels, which also lead to essential information loss.

The minimum variance quantization method (Heckbert, 1982b), divides the color space into boxes in the red, blue and green directions until obtaining a predefined number of colors. Then, the averages of the pixel values are represented as palette colors, as in uniform quantization.

The other example for this category is the popularity method (Clark, 1995) divides the color space into much smaller, and consequently many more, regions than 256 regions. For instance, $4 \times 4 \times 4$ in size (262,144 regions) is one possible implementation for the division. The average color of each region is represented as a candidate color for palette colors. In pallete, the regions with the highest frequencies of color are chosen as a member of pallete colors. That means this method can construct different palette spaces which improves the quality of reproduced image. Instead, some ignored colors with low frequencies cause the essential information loss same as in the median cut method.

The octree method (Gervautz and Purgathofer, 1990), subdivides the color space into levels of octants which uses the repeatedly selected different colors as initial color space. When the number of colors is higher than predefined number of colors, the adjacent colors with the least pixel numbers are merged into the closest color until obtaining the required number of clusters. Getting the similar results as in the median cut method, the octree method performs better than median cut method in terms of the speed and storage requirements.

Cheng and Yang (2001), proposed a color quantization method based on a fast dimensionality reduction technique. The color histogram is repeatedly divided into smaller boxes. The colors of each box are projected into a line which is defined by the mean color vector and the most distant color from the mean vector. Then, two basic colors are generated using the vectors which are comprised of the projection values for each box. The process is repeated until obtaining the predefined number of representative colors. After that, the average of all color vectors is represented as a representative color in each box and all representative colors form a color pallete space.

Yang and Tsai (1998) proposed a color quantization (i.e. image compression) method consisting of three steps such as quantization, thresholding and edge detection is based on moment-preserving principle. Firstly, an input image with 24 bits per pixel is quantized into 8 bits per pixel using moment-preserving thresholding technique (Tsai, 1985) where the color histogram is repeatedly sub-divided into smaller and smaller boxes, and two color values are computed automatically as two representative palette colors for every two separated boxes. After that, the quantized image is subdivided into $n \times n$ non-overlapping square blocks where two representative colors for each block are computed by moment-preserving thresholding. A bit-map is then created, including of 0 s and 1 s. In this way, the block pixels are assigned to the first or second color according to the Euclidean distance. Finally, the image is reproduced with a codebook of a 256-color palette.

2.2. *The Clustering-Based Methods*

The clustering-based methods have the disadvantage of high time consumption and they can be adversely affected from the initial conditions in general when comparing with the splitting methods; however, these methods generally perform better than the splitting methods in terms of finding the optimal solution on account of the fact that they can modify the centroids if it is needed (Omran, 2004). In fact, the clustering-based applications are widely used in some applications such as, spatial and medical image processing.

The K-means method (MacQueen, 1967), the most widely used method in this field, is proposed by Macqueen in 1967. Firstly, the initial centroids are randomly generated. After that, the pixels are assigned to the closest centroid and each centroid is then modified by averaging the pixel values in each class. This process is repeated until the predefined convergence. Being very simple, it is highly dependent on initial conditions.

The Fuzzy C-Means (FCM) method (Dunn, 1974), the soft version of the K-means, is proposed by Dunn so as to decrease the adverse effects of initial conditions. FCM generally performs better than K-means in terms of finding the optimal solution and FCM is less influenced by existence of uncertainty in the data set (Liew *et al.*, 2000). However, it might be highly affected from the noise and imaging artefacts (Forouzanfar *et al.*, 2010). Recently, the new versions of FCM such as, robust fuzzy C-means (RFCM) (Pham, 2001), possibilistic C-means (PCM) (Krishnapuram and Keller, 1993) and generalized

FCM (GFCM) (Jian and Miin-Shen, 2007) etc., were developed by modifying equations based on objective functions.

Bing *et al*. (2004) proposed a clustering method based on three steps. In first step, N number of initial colors is obtained by a clustering algorithm (BIRCH). In second step, the most convenient K colors are chosen from N number of colors according to different quantization tasks. Then, the left N–K colors are assigned to the closest colors in initial pallete to construct the final palette.

Evolutionary based algorithms were applied to the color quantization so as to decrease the negative effects of initial conditions. Freisleben and Schrader (1997) proposed a quantization method based on the combination of evolutionary algorithm (EA) and a standard search strategy. Firstly, a population representing color map was initialized. K-means was applied after each generation to improve the solutions and standard Euclidean distance error was chosen as the objective function. The performance of the EA&K-Means method was compared with two splitting methods such as, median cut and octree methods. The results showed that the combination of EA and K-means was superior to the others. The combination of the genetic algorithm (GA) and K-means (GCMA) was applied to the color quantization with the mean square error (MSE) as an objective function (Scheunders, 1997). In GCMA, K-means was applied to all chromosomes and then GA operations such as, single-point crossover and mutation operators were applied to improve the solutions. Omran and Engelbrecht (2005) applied the particle swarm optimization (PSO) algorithm with K-means to the color quantization (PSO-CIQ). In PSO-CIQ, MSE was also used as an objective function, but K-means was applied in a probabilistic manner after each generation to decrease the computation time. The results of the PSO-CIQ method were compared with the results of Kohonen's self organizing maps (SOM). From the obtained results,the PSO-CIQ method was shown to perform better than SOM. Additionally, SOM (Dekker, 1994; Papamarkos *et al*., 2002) and competitive learning (Celebi, 2009; Uchiyama and Arbib, 1994) could be given as examples for the other methods applied to the color quantization problem.

3. ABC Algorithm

Focusing on the collective behaviours which derives from the local interactions of the individuals with each other and with their environment,swarm intelligence (SI) has become an important research area to sort out problems (Birattari, 2007). The classical examples of SI are the bird flocks, fish schools, ants and bees. Especially from the beginning of the 2000s, researchers began to model the behaviours of honey bee swarms such as dance and communication, task allocation,collective decision, mating, nest site selection, marriage, foraging,floral and pheromone laying and navigation. These studies resulted many bee swarm intelligence based algorithms such as, the virtual bees algorithm (VBA) (Yang, 2005), the bees algorithm (BA) (Pham *et al*., 2005), BeeAdHoc (Wedde and Farooq, 2005), honey bee mating optimization (HMBO) (Haddad *et al*., 2006), the BeeHive (Wedde *et al*., 2004), bee system (BS) (Lucic and Teodorovic, 2001), bee colony optimization (BCO) (Teodorovic and Dell'orco, 2005) and the artificial bee colony algorithm

(ABC) (Karaboga, 2005). Being the most widely used one among all these algorithms, the ABC algorithm leads us to focus on the algorithm (Karaboga *et al.*, 2012a).

The ABC algorithm simulates the bee colony comprising three kinds of bees such as, employed bees, onlooker bees and scout bees. Being half of the number of colony size, the number of employed bees is equal to the number of onlooker bees in the colony. Each employed bee exploits only one food source and share the quality information of its food sources with onlooker bees waiting on the dance area in the hive. Onlooker bees are responsible for deciding on a food source to exploit based on the information shared by the employed bees. Scout bees either randomly explores the environment in order to find a new food source dependent on an internal motivation or based on possible external clues. In the hive, the exploration and exploitation processes are sequentially employed. For instance, a scout bee becomes an employed bee after exploring a food source and an employed bee becomes a scout bee after exploiting a food source.

A food source represents a solution and the nectar amount of a food source is related with the quality of the solution i.e. the fitness value. The main steps of the ABC algorithm can be described as follows:

Initialization phase: The food sources (x_i's) are randomly generated within the predefined range of the boundaries by Eq. (1):

$$x_{ij} = x_j^{\min} + rand(0,1)\left(x_j^{\max} - x_j^{\min}\right) \tag{1}$$

where $i = 1, \dots, SN$, SN is the number of food sources, $j = 1, \dots, D$, D is the number of parameters. $x_j^{\min}$ is the minimum and $x_j^{\max}$ is the maximum values of parameter j.

Employed bee phase: Each employed bee is associated with only one food source and it tries to modify the position of that food source by Eq. (2);

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \tag{2}$$

where j and k are randomly chosen parameter and neighbourhood, respectively; and ϕ_{ij} is a random number within $[-1, 1]$.

Being out of the predefined boundaries, the position is set to the closest side of the boundaries. After producing the solution v_i, the nectar amount (fitness value) of the food source v_i for minimization problems is computed by Eq. (3):

$$fitness_i = \begin{cases} \frac{1}{1+fit_i}, & fit_i \geqslant 0, \\ 1 + abs(fit_i), & fit_i < 0, \end{cases} \tag{3}$$

where fit_i is the cost value (value of objective function) of the food source v_i. For maximization problems, the cost value can be directly used as fitness value.

After the calculation of fitness values, the greedy approach is applied to the v_i and x_i food sources. If the fitness value of v_i is greater than x_i, the employed bee memorizes v_i as a new food source and leaves x_i. Otherwise, the employed bee continues to keep the current food source. When x_i is not improved, its counter representing the number of trials is incremented by 1; otherwise, it is set to 0.

Onlooker bee phase: After all employed bees complete their exploitation processes, they share information concerning the nectar amount and the positions of food sources with onlooker bees via waggle dance on the dance area. In other words, multiple interactions are modelled between the employed bees and onlooker bees in ABC. An onlooker bee selects a food source based on evaluating the probability of the nectar amount from the information shared by employed bees. In ABC, tournament selection is employed to evaluate the probability, defined by Eq. (4);

$$p_i = \frac{fitness_i}{\sum_{i=1}^{SN} fitness_i} \tag{4}$$

where $fitness_i$ is calculated by Eq. (3).

To apply the probabilistic selection, a random number within the range [0, 1] is generated for every food source. After that, if the generated random number for the food source is smaller than the related p_i value (calculated by Eq. (4)), the associated onlooker bee starts to modify the position of the food source and finds a neighbouring food source by Eq. (2) as in the case of the employed bee phase. After that, greedy approach is also applied between the neighbouring food source and the related food source. According to the comparsion of the fitness values of neighbouring and old food sources, the onlooker bee memorizes the neighbouring food source or keeps the old one. When x_i is not improved, its counter representing the number of trials is incremented by 1; otherwise, it is set to 0.

The aim of applying the probabilistic selection is to increase the chance of selecting the food sources with the high nectar amount (fitness value) that can be accepted as a positive feedback feature of the ABC algorithm. In this way, the chance of finding the most valuable food sources is also increased.

Scout bee phase: After the employed bee and onlooker bee phases, the abandoned food source is replaced with new randomly produced food sources (generated by Eq. (1)) by the scouts. To decide a food source as an abandoned food source or not, its counter representing the number of trials is checked in this phase. The food source the counter of which is greater than the predefined number of value referred as “limit” is assigned as abandoned, and then a scout randomly discovers a new food source and it is replaced with the abandoned one. This process represents the property of negative feedback mechanism and fluctuation in the self-organization of the ABC algorithm (Akay and Karaboga, 2012).

4. Color Quantization with ABC (CQ-ABC)

The mathematical description of color quantization can be defined as follows: quantization is a mapping process from some finite of color sets T with colors M onto T' with colors N i.e. $q : T \rightarrow T'$ where $T \subset R^n$, $T' \subset R^n$ and $N < M$. The main steps of color quantization with the artificial bee colony algorithm (CQ-ABC) are described as follows:

The two well-known color spaces such as RGB and L*a*b (CIELAB) are selected for the quantization process. A set of food sources (solutions) is randomly chosen from the original image. For RGB color space, each parameter of solution consists of three components such as red, green and blue. For L*a*b color space, each parameter of solution consists of three components: luminosity layer ‘L*’, chromaticity-layer ‘a*’ and chromaticity-layer ‘b*’. However, luminosity layer ‘L*’ is not incorporated to the quantization process since all of the color information is appeared in the ‘a*’ and ‘b*’ layers.

In color quantization, a solution represents an initial color space and the dimension of the solution represents the predefined number to be divided into specified colors. In the structure of the RGB format, a solution is defined as $x_i = (x_{i1}, x_{i2}, x_{i3}, \dots, x_{iD})$, where x_i is the ith solution of the population and $x_{iD} = [R_{iD}, G_{iD}, B_{iD}]$ is a vector representing the Dth centroid of solution i. As for the structure of L*a*b format, the dimension of a solution is represented as $x_i = (x_{i1}, x_{i2}, x_{i3}, \dots, x_{iD})$ where x_i is the ith solution of the population and $x_{iD} = [a_{iD}, b_{iD}]$ is a vector representing the Dth centroid of solution i.

The main mechanism of the quantization are same in both RGB and L*a*b color spaces. Before the neighborhood search of the ABC algorithm, K-means is applied to the each solution in a probabilistic manner with a user specified number p_{KM} in order to minimize the adverse effects of randomly generated initial solutions which leads local convergence problem. The K-means method is inserted into the CQ-ABC as used by Omran and Engelbrecht (2005) for PSO based color quantization. For the evaluation of the population, each pixel is assigned to the closest cluster centroid and mean square error (MSE) is employed as the objective function of RGB and L*a*b color spaces which are defined by Eqs. (5) and (6);

$$MSE_{RGB} = \frac{1}{N_p} \sum_{k=1}^{K} \sum_{\forall z_p \in C_k} \left(R_p - R'_k\right)^2 + \left(G_p - G'_k\right)^2 + \left(B_p - B'_k\right)^2 \tag{5}$$

where $z_p = [R_p, G_p, B_p]$ is the pth three dimensional pixel of image, $C_k = [R'_k, G'_k, B'_k]$ is the kth three dimensional centroid, N_p is the number of pixels in the image and K is the total number of clusters.

$$MSE_{\mathrm{L^*a^*b}} = \frac{1}{N_p} \sum_{k=1}^{K} \sum_{z_p \in C_k} \left(a_p - a'_k\right)^2 + \left(b_p - b'_k\right)^2 \tag{6}$$

where $z_p = [a_p, b_p]$ is the pth two dimensional pixel of image and $C_k = [a'_k, b'_k]$ is the kth two dimensional centroid.

The quality of each solution is evaluated by Eq. (6);

$$f(x_i) = \begin{cases} MSE_{RGB}(x_i) & \text{if color space is } RGB \\ MSE_{\mathrm{L^*a^*b}}(x_i) & \text{if color space is L*a*b} \end{cases} \tag{7}$$

After the evaluation process, the ABC algorithm is implemented to improve the solutions until the stopping criterion is satisfied. Then, the best solution is selected as a palette

```
begin
    randomly initialize each solution with K number of centroids from the orginal image;
    for cycle ← 1 to MCN do
        foreach employed bee i do
            Apply K-means to the solution i for few iterations in a probabilistic manner;
            foreach pixel z_p do
                foreach cluster m_{i,k} do
                    Calculate D^2(z_p, m_{i,k}) = (R_p − R'_{i,k})^2 + (G_p − G'_{i,k})^2 + (B_p − B'_{i,k})^2 ;
                    Assign z_p to the centroid k which has the minimum D^2(z_p, m_{i,k}) value;
                end
                Calculate the objective function by (7);
            end
            Update the solution i by (2) and (3);
        end
        foreach onlooker bee do
            Select a solution j depending on the probability by (4);
            Apply K-means to the solution j for few iterations in a probabilistic manner;
            foreach pixel z_p do
                foreach cluster m_{j,k} do
                    Calculate D^2(z_p, m_{j,k}) = (R_p − R'_{j,k})^2 + (G_p − G'_{j,k})^2 + (B_p − B'_{j,k})^2 ;
                    Assign z_p to the centroid k which has the minimum D^2(z_p, m_{j,k}) value;
                end
                Calculate the objective function by (7);
            end
            Update the solution j by (2) and (3);
        end
        if the unsuccesful trials of a solution > "limit" then
            generate a new solution by scout bee using (1);
        end
    end
end
```

Fig. 1. The pseudo code of the CQ-ABC algorithm.

color space. Finally, the peak signal-to-quantization-noise ratio (PSQNR) (Savic *et al.*, 2012), a measurement of distortion between the original and output images, is calculated through the best solution by Eq. (8);

$$PSQNR = 20\log_{10} Max_{im} - 10\log_{10} MSE \tag{8}$$

where Max_{im} is the maximum pixel intensity of the image. The detailed pseudo code of the CQ-ABC method is presented in Fig. 1.

5. Experimental Results

The CQ-ABC is applied to the four benchmark images: Jet, Lena, Mandril and Pepper into 16, 32, 64 and 128 colors, which are presented in Figs. 2, 3 and 4, respectively. The analysis of the proposed method is demonstrated by comparing it with the CQ-PSO, K-means, FCM and minimum variance methods in terms of RGB color space and by comparing it with the CQ-PSO, K-means and FCM methods in terms of L*a*b color space. Evaluated

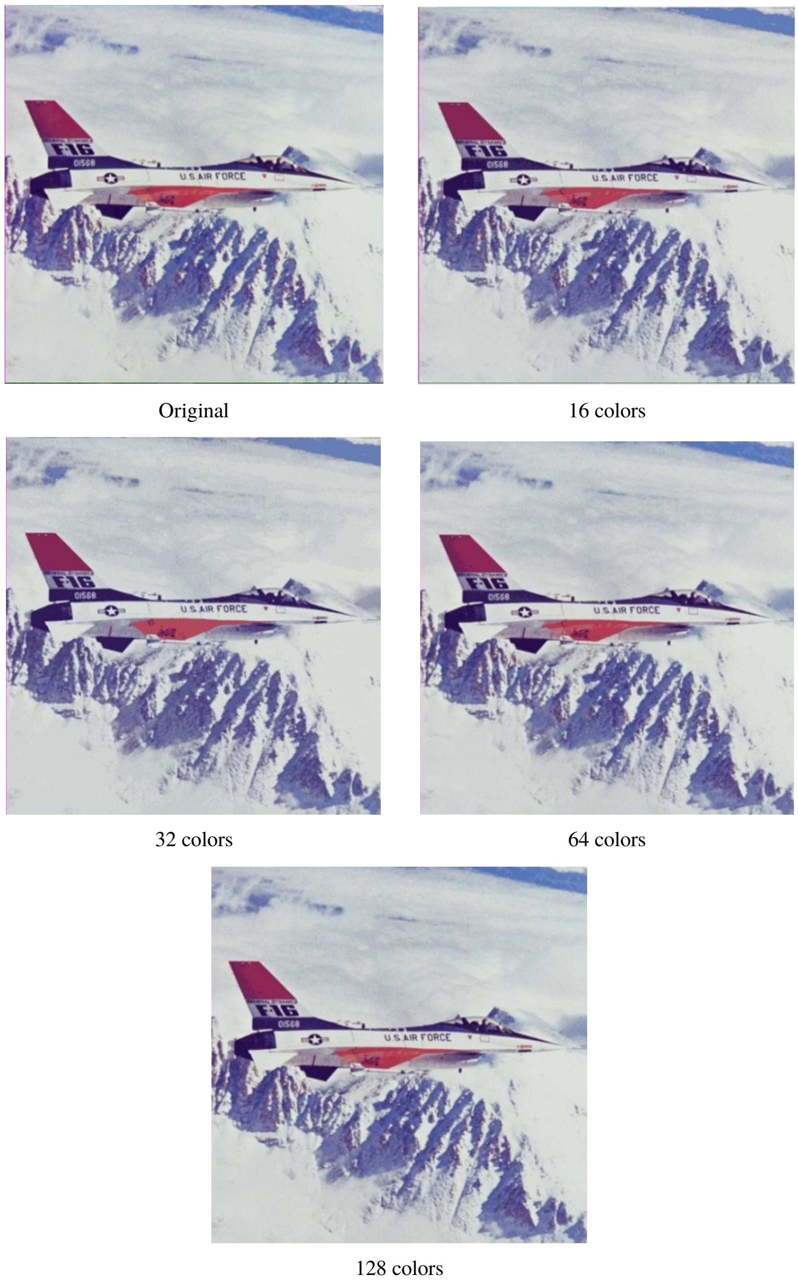


Fig. 2. The visual results for the jet image is obtained by CQ-ABC.

through the RGB and L*A*B spaces, the evaluation criterions are based on the mean square error and the peak signal-to-quantization-noise ratio (PSQNR). The results are presented in Tables 1–4 over the 30 simulations in terms of the mean values and standard deviations given in the parenthesis.

Original

16 colors

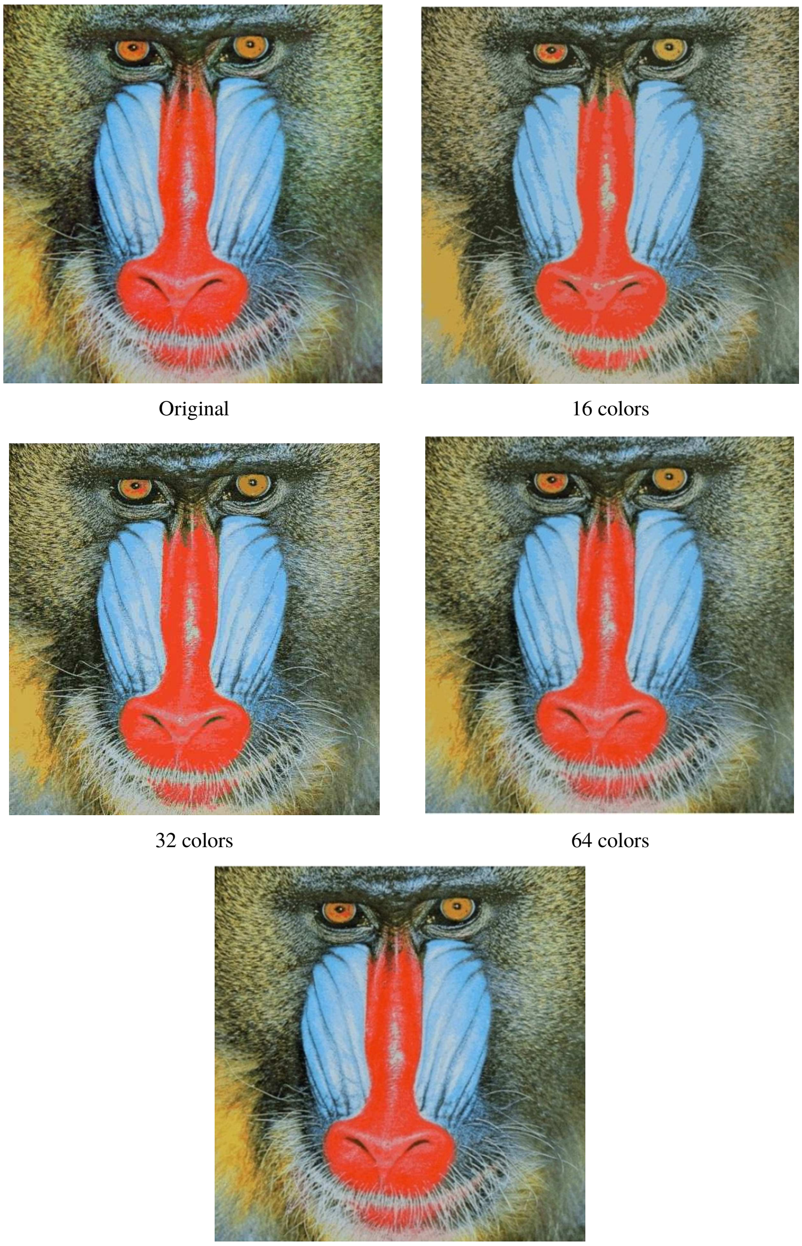
32 colors

64 colors

128 colors

Fig. 3. The visual results for the Lena image is obtained by CQ-ABC.

In the experiments of color quantization, the following parameters are used for the CQ-ABC, CQ-PSO, K-means and FCM methods: the number of food sources is chosen as 20 and the limit value is chosen as 50 for CQ-ABC; the number of particles is taken as 20 for CQ-PSO. p_{KM} is chosen as 0.1 and K-means is applied for 50 iterations in CQ-



Original
16 colors
32 colors
64 colors
128 colors

Fig. 4. The visual results for the mandril image is obtained by CQ-ABC.

ABC and CQ-PSO. For a fair comparison, the total evaluation number is taken same for all algorithms and cases. Therefore, the number of iterations (cycles) is set to 50 such that the number of evaluations is 1000 and the number of iterations is selected as 1000 for FCM and K-means. The parameters of CQ-PSO are selected as used in Omran *et al*. (2006) for

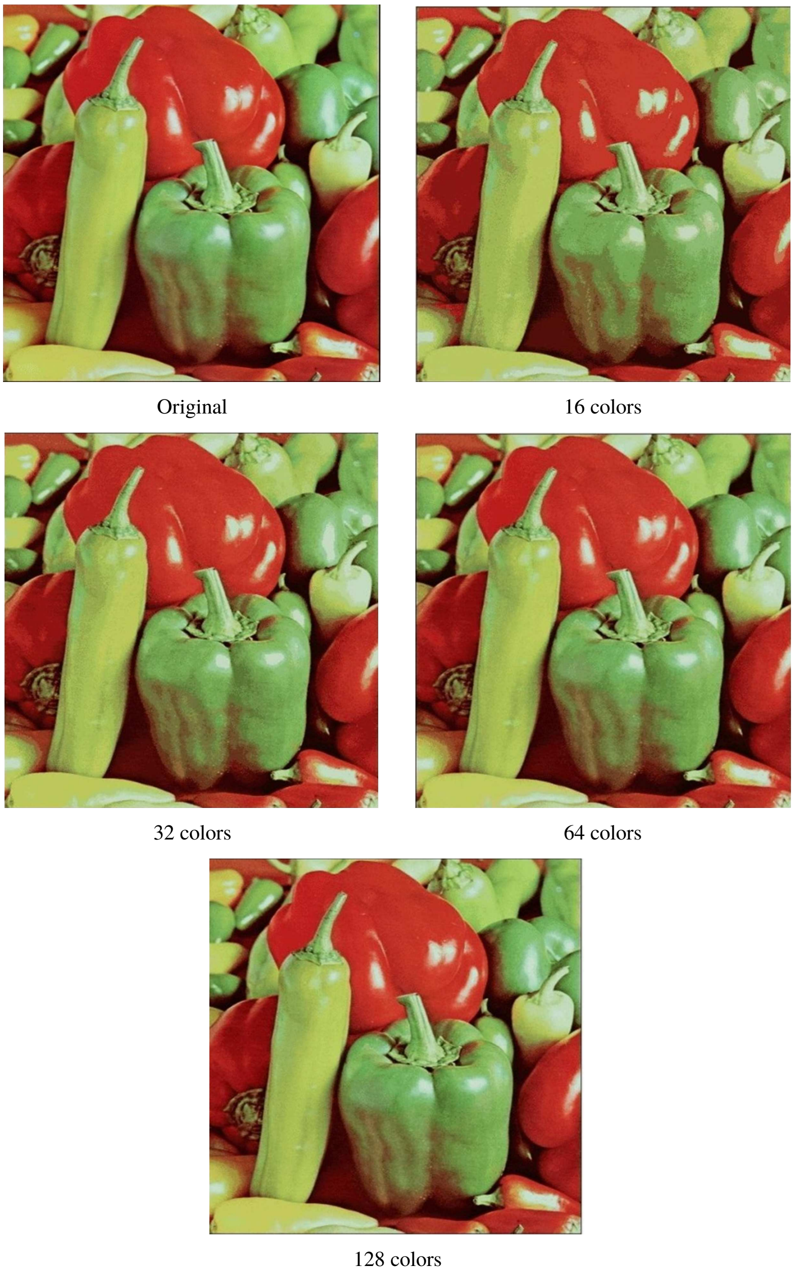


Fig. 5. The visual results for the pepper image is obtained by CQ-ABC.

the experiments of image clustering: $c_1 = 1.49$, $c_2 = 1.49$, $w_{start} = 0.72$, $w_{end} = 0.4$ and $V_{max} = 255$; the parameters of GA are selected as crossover rate $= 0.8$ and mutation rate $= 0.2$. The parameter determining the influence of the weights in FCM is empirically set to 1.1.

Table 1
The results of MSE values for RGB color quantization.

Images	K	CQ-ABC	CQ-PSO	FCM	K-means	Minimum variance
Jet	16	124.100 (3.687)	126.208 (3.968)	124.297 (7.789)	153.824 (6.412)	138.3569
	32	62.028 (0.095)	62.374 (0.480)	62.063 (0.177)	62.303 (0.496)	67.6027
	64	37.128 (0.587)	37.342 (0.641)	37.101 (0.231)	38.146 (0.433)	41.9033
	128	25.018 (0.350)	25.159 (1.140)	23.637 (0.434)	26.406 (0.358)	26.587
Lena	16	159.468 (0.944)	161.329 (2.697)	160.891 (0.978)	164.954 (4.576)	176.605
	32	83.047 (0.230)	83.860 (0.847)	83.101 (0.454)	84.632 (1.050)	94.562
	64	47.224 (0.186)	47.413 (0.487)	47.166 (0.164)	48.330 (0.898)	52.920
	128	28.405 (0.127)	28.532 (0.248)	27.996 (0.069)	28.988 (0.314)	31.742
Mandril	16	508.500 (0.149)	509.795 (2.019)	511.246 (6.201)	512.060 (5.094)	571.894
	32	283.781 (0.418)	286.053 (2.266)	287.137 (2.917)	287.817 (3.268)	326.267
	64	162.412 (0.326)	163.317 (1.131)	166.828 (1.635)	164.579 (1.441)	184.968
	128	97.844 (0.177)	98.448 (0.582)	98.686 (0.279)	98.642 (0.659)	113.225
Pepper	16	356.538 (0.005)	357.333 (1.024)	358.681 (2.388)	358.676 (2.715)	390.544
	32	203.169 (0.608)	205.048 (2.054)	206.742 (2.447)	205.338 (1.756)	217.383
	64	118.177 (0.388)	118.519 (0.714)	120.185 (0.969)	119.846 (1.527)	130.721
	128	69.883 (0.371)	70.436 (0.651)	72.312 (0.543)	71.374 (1.102)	79.192

Table 2
The results of PSQNR values for RGB color quantization.

Images	K	CQ-ABC	CQ-PSO	FCM	K-means	Minimum variance
Jet	16	27.194 (0.128)	27.122 (0.137)	27.193 (0.252)	26.264 (0.193)	26.720
	32	30.204 (0.006)	30.181 (0.033)	30.202 (0.012)	30.186 (0.034)	29.831
	64	32.434 (0.068)	32.409 (0.074)	32.437 (0.027)	32.316 (0.049)	31.908
	128	34.148 (0.061)	34.128 (0.196)	34.396 (0.080)	33.914 (0.059)	33.884
Lena	16	26.104 (0.026)	26.054 (0.071)	26.066 (0.026)	25.959 (0.120)	25.661
	32	28.937 (0.012)	28.895 (0.043)	28.935 (0.024)	28.856 (0.054)	28.374
	64	31.389 (0.017)	31.372 (0.044)	31.394 (0.015)	31.289 (0.080)	30.895
	128	33.596 (0.019)	33.578 (0.038)	33.660 (0.011)	33.509 (0.047)	33.114
Mandril	16	21.068 (0.001)	21.057 (0.017)	21.045 (0.052)	21.038 (0.043)	20.558
	32	23.601 (0.006)	23.566 (0.034)	23.550 (0.044)	23.540 (0.049)	22.995
	64	26.025 (0.009)	26.001 (0.030)	25.908 (0.042)	25.967 (0.038)	25.460
	128	28.225 (0.008)	28.199 (0.026)	28.188 (0.012)	28.190 (0.029)	27.591
Pepper	16	22.610 (0.000)	22.600 (0.012)	22.584 (0.028)	22.583 (0.032)	22.214
	32	25.052 (0.013)	25.012 (0.043)	24.977 (0.051)	25.006 (0.037)	24.758
	64	27.405 (0.014)	27.393 (0.026)	27.332 (0.035)	27.345 (0.055)	26.967
	128	29.687 (0.023)	29.653 (0.040)	29.539 (0.033)	29.596 (0.067)	29.144

Considering implementation of color quantization to the RGB lab space, Tables 1 and 2 reveal that the CQ-ABC method acquires the best optimal values in terms of minimizing MSE and maximizing PQNR in most experiment cases. Particularly, CQ-ABC cannot obtain the best values only for jet and Lena in terms of quantizing into 64 and 128 colors. Furthermore, CQ-ABC method also gets the best standard deviation values in almost all cases which shows the robustness of the proposed method. Tables 1 and 2 also reveal that CQ-PSO method gets the second order for the images Mandril and pepper, and it

Table 3
The results of MSE values for L*a*b color quantization.

Images	K	CQ-ABC	CQ-PSO	FCM	K-means
Jet	16	9.45 (0.09)	9.57 (0.25)	12.37 (1.16)	11.05 (0.75)
	32	4.83 (0.06)	4.88 (0.09)	4.91 (0.16)	5.98 (0.47)
	64	2.57 (0.04)	2.59 (0.07)	2.48 (0.07)	3.84 (0.43)
	128	1.28 (0.02)	1.33 (0.04)	1.30 (0.02)	2.43 (0.33)
Lena	16	6.23 (0.05)	6.43 (0.21)	6.28 (0.07)	6.57 (0.30)
	32	3.38 (0.04)	3.44 (0.09)	3.51 (0.15)	3.58 (0.16)
	64	1.82 (0.02)	1.87 (0.05)	2.04 (0.08)	1.92 (0.06)
	128	0.94 (0.01)	0.99 (0.03)	1.14 (0.05)	1.00 (0.03)
Mandril	16	25.34 (0.06)	25.50 (0.30)	25.51 (0.15)	25.67 (0.37)
	32	12.75 (0.07)	12.86 (0.24)	12.67 (0.09)	13.35 (0.42)
	64	6.91 (0.07)	7.14 (0.18)	6.63 (0.03)	7.32 (0.25)
	128	3.71 (0.05)	3.90 (0.22)	3.50 (0.03)	3.90 (0.13)
Pepper	16	24.93 (0.04)	25.13 (0.18)	25.07 (0.19)	25.60 (0.59)
	32	12.24 (0.09)	12.44 (0.27)	12.25 (0.16)	12.79 (0.32)
	64	6.27 (0.06)	6.42 (0.21)	6.09 (0.03)	6.74 (0.26)
	128	3.27 (0.04)	3.38 (0.16)	3.37 (0.05)	3.45 (0.10)

gets the third order position for jet and Lena images. In other words, CQ-PSO is not very convenient in terms of minimizing MSE and maximizing PSQNR. On the other hand, minimum variance method gets the worst values against the other algorithms so that can be inferred that the splitting based methods are needed to be improved to reach adequate performances. Moreover, FCM performs well in jet and Lena images while quantizing into 64 and 128 colors. In addition, FCM performs better than K-means almost in all cases.

When analysing the implementation of color quantization to the L*a*b space, Tables 3 and 4 demonstrate that CQ-ABC method also obtains the best optimal values in terms of MSE and PSQNR in most experiment cases. Only for the Mandril image and some cases of quantizing into 64 colors, the performance of the CQ-ABC method cannot get the best values against FCM. Moreover, the CQ-ABC method has the 11 best performances over 16 experiments. The other 5 best performances are provided by FCM. The CQ-ABC method also satisfies the best minimum standard deviations almost in all cases, which shows the robustness of the CQ-ABC method. The performances of the other methods such as CQ-PSO and K-means are not adequate against CQ-ABC and FCM in most cases. Therefore, the methods such as CQ-ABC, FCM, PSO and K-means are ranked as first, second, third and fourth positions, respectively as in the implementation of RGB color space.

6. Conclusion

In this paper, a new color-based quantization method is proposed based on the artificial bee colony (ABC) algorithm and it is applied to the both RGB and CIELAB spaces. To our knowledge, ABC is applied for the first time to the color quantization problem. In addition, it is tried to be given with a detailed literature review of color quantization methods. The

Table 4
The results of PSQNR values for L*a*b color quantization.

Images	K	CQ-ABC	CQ-PSO	FCM	K-means
Jet	16	36.812 (0.043)	36.761 (0.111)	35.666 (0.457)	36.141 (0.294)
	32	39.726 (0.053)	39.684 (0.088)	39.658 (0.143)	38.811 (0.318)
	64	42.474 (0.073)	42.441 (0.111)	42.631 (0.121)	40.750 (0.471)
	128	45.482 (0.074)	45.318 (0.147)	45.440 (0.064)	42.756 (0.662)
Lena	16	36.915 (0.038)	36.777 (0.142)	36.882 (0.050)	36.685 (0.194)
	32	39.571 (0.047)	39.501 (0.119)	39.419 (0.179)	39.319 (0.188)
	64	42.249 (0.045)	42.145 (0.120)	41.761 (0.172)	42.021 (0.146)
	128	45.120 (0.049)	44.892 (0.114)	44.858 (0.126)	44.267 (0.199)
Mandril	16	31.982 (0.009)	31.955 (0.051)	31.926 (0.062)	31.954 (0.025)
	32	34.964 (0.024)	34.930 (0.079)	34.991 (0.031)	34.766 (0.135)
	64	37.623 (0.043)	37.484 (0.109)	37.803 (0.020)	37.377 (0.145)
	128	40.325 (0.058)	40.119 (0.245)	40.578 (0.044)	40.114 (0.146)
Pepper	16	31.654 (0.007)	31.618 (0.031)	31.628 (0.033)	31.538 (0.099)
	32	34.742 (0.031)	34.673 (0.093)	34.740 (0.055)	34.554 (0.109)
	64	37.647 (0.042)	37.543 (0.144)	37.774 (0.022)	37.336 (0.170)
	128	40.474 (0.065)	40.337 (0.199)	40.239 (0.126)	40.344 (0.058)

proposed method is compared with the well-known algorithms such as, K-means, FCM, CQ-PSO and the minimum variance methods based on mean square error and peak signal-to-quantization-noise ratio. From the obtained results, the minimum variance method, one of the most widely used splitting methods, is indicated to have the worst performances. Therefore, the splitting methods are generally fast and simple; however they cannot obtain the optimal values. The results also summarize that the proposed CQ-ABC algorithm generally performs better than the others. It is thought that new objective functions or hybrid models might improve the performance of the color quantization. So, as a future work, it is planned to propose new objective functions and hybrid approaches.

References

Akay, B., Karaboga, D. (2012). A modified artificial bee colony algorithm for realparameter optimization. *Information Sciences*, 192, 120–142.

Bing, Z., Junyi, S., Qinke, P. (2004). An adjustable algorithm for color quantization. *Pattern Recognition Letters*, 25(16), 1787–1797.

Birattari, M. (2007). Swarm intelligence. *Scholarpedia*, 2, 1462.

Braquelaire, J.P., Brun, L. (1997). Comparison and optimization of methods of color image quantization. *IEEE Transactions on Image Processing*, 6(7), 1048–1052.

Celebi, M.E., (2009). An effective color quantization method based on the competitive learning paradigm. In: *Proceedings of International Conference on Image Processing, Computer Vision, and Pattern Recognition*, Vol. 2, pp. 876–880.

Celebi, M.E., Wen, Q., Chen, J. (2011). Color quantization using c-means clustering algorithms. In: *Proceedings of 18th IEEE International Conference on Image Processing (ICIP)*, pp. 1729–1732.

Cheng, S.-C., Yang, C.-K. (2001). A fast and novel technique for color quantization using reduction of color space dimensionality. *Pattern Recognition Letters*, 22(8), 845–856.

Clark, D. (1995). The popularity algorithm. *Dr. Dobb's Journal*, 121–128.

Dekker, A.H. (1994). Kohonen neural networks for optimal colour quantization. *Network: Computation in Neural Systems*, 5(3), 351–367.

Dunn, J.C. (1974). Well separated clusters and optimal fuzzy partitions. *Journal of Cybernetics*, 4, 95–104.

Forouzanfar, M., Forghani, N., Teshnehlab, M. (2010). Parameter optimization of improved fuzzy c-means clustering algorithm for brain MR image segmentation. *Engineering Applications of Artificial Intelligence*, 23(2), 160–168.

Freisleben, B., Schrader, A. (1997). An evolutionary approach to color image quantization. In: *Proceedings of IEEE International Conference on Evolutionary Computation*, pp. 459–464.

Gervautz, M., Purgathofer, W. (1990). A simple method for color quantization: octree quantization. In: Andrew, S.G. (Ed.), *Graphics Gems*. Academic Press Professional, pp. 287–293.

Haddad, O., Afshar, A., Mari?o, M. (2006). Honey-Bees Mating Optimization (HBMO) algorithm: a new heuristic approach for water resources optimization. *Water Resources Management*, 20(5), 661–680.

Hancer, E., Ozturk, C., Karaboga, D. (2012). Artificial bee colony based image clustering method. In: *Proceedings of IEEE Congress on Evolutionary Computation, (CEC 2012), Brisbane, Australia*, pp. 1–5.

Heckbert, P. (1982a). Color image quantization for frame buffer display. In: *Proceedings of 9th Annual Conference on Computer Graphics and Interactive Techniques, Boston, Massachusetts, United States*, pp. 297–307.

Heckbert, P. (1982b). Color image quantization for frame buffer display. *Computer Graphics*, 16(3), 297–307.

Hill, F.S.J. (1990). *Computer Graphics*. Macmillan, London.

Jian, Y., Miin-Shen, Y. (2007). A generalized fuzzy clustering regularization model with optimality tests and model complexity analysis. *IEEE Transactions on Fuzzy Systems*, 15(5), 904–915.

Karaboga, D. (2005). An idea based on honey bee swarm for numerical optimization. *Technical report-TR06*, Erciyes University, Engineering Faculty, Computer Engineering Department.

Karaboga, D., Basturk, B. (2008). On the performance of Artificial Bee Colony (ABC) algorithm. *Applied Soft Computing*, 8(1), 687–697.

Karaboga, D., Ozturk, C. (2009). Neural networks training by Artificial Bee Colony algorithm on pattern classification. *Neural Network World*, 19(3), 279–292.

Karaboga, D., Ozturk, C. (2011). A novel clustering approach: Artificial Bee Colony (ABC) algorithm. *Applied Soft Computing*, 11(1), 652–657.

Karaboga, D., Gorkemli, B., Ozturk, C., Karaboga, N. (2012a). A comprehensive survey: Artificial Bee Colony (ABC) algorithm and applications. *Artificial Intelligence Review*.

Karaboga, D., Okdem, S., Ozturk, C. (2012b). Cluster based wireless sensor network routing using Artificial Bee Colony algorithm. *Wireless Networks*, 18(7), 847–860.

Krishnapuram, R., Keller, J.M. (1993). A possibilistic approach to clustering. *IEEE Transactions on Fuzzy Systems*, 1(2), 98–110.

Kruger, A. (1994). Median-cut color quantization. *Dr. Dobb's Journal*, 46–54, 91–92.

Liew, A.W.C., Leung, S.H., Lau, W.H. (2000). Fuzzy image clustering incorporating spatial continuity. *IEEE Proceedings Vision, Image and Signal Processing*, 147(2), 185–192.

Lucic, P., Teodorovic, D., (2001). Bee system: modeling combinatorial optimization transportation engineering problems by swarm intelligence. In: *Proceedings of Preprints of the TRISTAN IV Triennial Symposium on Transportation Analysis, Sao Miguel, Azores Islands, Portugal*, pp. 441–445.

Savic, M., Peric, Z., Dincic, M. (2012). An algorithm for grayscale images compression based on the forward adaptive quantizer designed for signals with discrete amplitudes. *Electronics and Electrical Engineering*, 118(2), 13–16.

Ma, M., Liang, J., Guo, M., Fan, Y., Yin, Y. (2011). SAR image segmentation based on Artificial Bee Colony algorithm. *Applied Soft Computing*, 11(8), 5205–5214.

MacQueen, J. (1967). Some methods for classification and analysis of multivariate observations. In: *Proceedings of 5th Symposium on Mathematical Statistics and Probability*, pp. 281–297.

Omran, M. (2004). *Particle Swarm Optimization Methods for Pattern Recognition and Image Processing*. University of Pretoria, Environment and Information Technology.

Omran, M., Engelbrecht, A. (2005). A color image quantization algorithm based on particle swarm optimization. *Informatica*, 29, 261–269.

Omran, M., Engelbrecht, A., Salman, A. (2006). Particle swarm optimization for pattern recognition and image processing. In: Abraham, A., Grosan, C., Ramos, V. (Eds.), *Swarm Intelligence and Data Mining*. SCI Series 'Studies in Computational Intelligence'. Springer, Berlin.

Ozturk, C., Karaboga, D., Gorkemli, B. (2011). Probabilistic dynamic deployment of wireless sensor networks by artificial bee colony algorithm. *Sensors*, 11(6), 6056–6065.

Papamarkos, N., Atsalakis, A.E., Strouthopoulos, C.P. (2002). Adaptive color reduction. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, 32(1), 44–56.

Pham, D., Ghanbarzadeh, A., Koc, E., Otri, S., Rahim, S., Zaidi, M. (2005). *The Bees Algorithm, Manufacturing Engineering Centre*. Cardiff University, UK.

Pham, D.L. (2001). Spatial models for fuzzy clustering. *Computer Vision and Image Understanding*, 84(2), 285–297.

Samet, R., Hancer, E. (2012). A new approach to the reconstruction of contour lines extracted from topographic maps. *Journal of Visual Communication and Image Representation*, 23(4), 642–647.

Scheunders, P. (1997). A genetic c-means clustering algorithm applied to color image quantization. *Pattern Recognition*, 30(6), 859–866.

Teodorovic, D., Dell'orco, M. (2005). Bee colony optimization – a cooperative learning approach to complex transportation problems. In: *Proceedings of 16th Mini-EURO Conference on Advanced OR and AI Methods in Transportation*, pp. 51–60.

Tsai, H. (1985). Moment-preserving thresholding: a new approach. *Computer Vision, Graphics, and Image Processing*, 29(3), 377–393.

Uchiyama, T., Arbib, M.A. (1994). An algorithm for competitive learning in clustering problems. *Pattern Recognition*, 27(10), 1415–1421.

Wedde, H., Farooq, M. (2005). The wisdom of the hive applied to mobile ad-hoc networks. In: *Proceedings of Swarm Intelligence Symposium SIS 2005*, pp. 341–348.

Wedde, H., Farooq, M., Zhang, Y. (2004). BeeHive: An Efficient Fault-Tolerant Routing Algorithm Inspired by Honey Bee Behavior. *LNCS*, Vol. 3172. Springer, Heidelberg, pp. 83–94.

Yang, C.-K., Tsai, W.-H. (1998). Color image compression using quantization, thresholding, and edge detection techniques all based on the moment-preserving principle. *Pattern Recognition Letters*, 19(2), 205–215.

Yang, X., 2005. *Engineering Optimizations via Nature-Inspired Virtual Bee Algorithms*. Springer, Berlin.

C. Ozturk received the BS degree in the Department of Computer Engineering from Erciyes University, Turkey in 2000; the MS degree in Electrical and Computer Engineering from Rutgers University, USA, in 2004; and the PhD degree in the Department of Computer Engineering from Erciyes University, in 2011. He is currently working as an Assistant Professor in Erciyes University. His research interests include training neural networks, clustering, and optimization in wireless sensor networks and bioinformatics.

E. Hancer received the BS degree in the Department of Mathematics and Computer Science from Cankaya University, Turkey in 2009, and the MS degree in Computer Engineering from Erciyes University, Turkey, in 2012. He is currently a PhD student and a research assistant at the Department of Computer Engineering, Erciyes University. His research interests include map image processing, clustering algorithms and discrete optimization.

D. Karaboga received the BSc degree from the Department of Electronics Engineering, Erciyes University, Turkey, in 1983, the MSc degree in 1988 from the Department of Electronics and Communication Engineering, Istanbul Technical University, Turkey, and the PhD degree in 1994 from Systems Engineering Department, University of Wales, College of Cardiff, UK. He is currently a Professor at the Department of Computer Engineering, Erciyes University. His research areas include optimization, fuzzy systems, neural networks and engineering applications of intelligent methods.

Spalvinis vaizdų kvantavimas: trumpa apžvalga ir taikymas pasitelkiant dirbtinės bičių kolonijos algoritmą

Celal OZTURK, Emrah HANCER, Dervis KARABOGA

Spalvinis kvantavimas – tai procesas, kurio metu skaitmeniniame vaizde sumažinamas spalvinių atspalvių kiekis. Pagrindinis kvantavimo proceso tikslas yra išsaugoti vaizde sukauptą reikšmingą informaciją. Kitaip tarus, spalvinio kvantavimo procesas neturi iššaukti svarbios informacijos praradimų vaizde. Šiame straipsnyje pateikiama trumpa su spalviniu kvantavimu susijusių požiūrių apžvalga, pristatomi naujas dirbtinės bičių kolonijos algoritmu (ABC) grindžiamas spalvinio kvantavimo metodas bei jo taikymo keturiems etaloniniams vaizdams rezultatai. Siūlomo metodo privalumai atskleidžiami, lyginant jį su kitais praktikoje plačiai naudojamais spalvinio kvantavimo metodais, būtent: K-vidurkiai, neraiškieji C-vidurkiai (FCM), mažiausia dispersija bei dalelių spiečiaus optimizavimas (PSO).