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A new fast color reduction method based on adaptive histogram binning approach

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Abstract- Most color reduction methods that are based on image clustering in a 3D color space have extremely high computational costs, especially for large size images. In this paper, a new fast adaptive color reduction method is proposed which, computationally, is independent of the image size and reduces the pixel depth from 24 bits (used to represent tristimulus values in the most commonly hardware-oriented RGB model) to a maximum of 15 bits. To achieve this purpose, by introducing a new hybrid cost function and using a modified version of the Gravitational Search Algorithm (GSA), an adaptive histogram binning approach has been developed. Although the cube re-quantization accuracy in the histogram binning approach is lower compared to the 3D data clustering method, it leads to a significant reduction in computational cost. In this paper, while taking this advantage, we seek to reduce re-quantization error using the adaptive histogram binning of RGB color components. Despite a significant reduction in pixel depth, the proposed color reduction approach, due to the adaptive reduction of image colors, results in an appropriate color reduction for a wide variety of images.

Keywords- Swarm Intelligence, Gravitational Search Algorithm, Color Reduction, Adaptive Histogram Binning.

I. INTRODUCTION

The RGB model is the most commonly used hardware-oriented model for color monitors and a broad class of color video cameras. Represented images in the RGB color model consist of three 8-bit components (one for each primary color). Under this condition, a pixel depth of 24 bits has been used to tristimulus values representation in the RGB space. The total number of colors in a 24-bit RGB color cube is $(2^8)^3$=16777216. In many scene images, there is no need for such a high precision uniform quantization of the color cube. On the other hand, reducing the number of image colors, especially in high-resolution images with high color variations, reduces storage space and computational cost and also increases the accuracy of subsequent image processing algorithms [1].

In a comprehensive approach to developing an effective color reduction method that can apply to a wide range of color images, it should be developed adaptively, and with full consideration of image color content. So far, several color reduction methods have been developed that most of them are based on non-uniform re-quantization of the color cube (using image color content) [2], [3], [4], and [5]. Many color reduction algorithms perform clustering on three-dimensional color data [2], [4], [6], [7], and [8]. In these methods, the output colors are chosen appropriately for each image, but the number of output colors must be selected by the user. Also, these methods are very time-consuming for large size images and reduce accuracy [2], [4], [6], and [8]. Also, the number of iteration in the algorithms is dependent on the image size [2]. Although these algorithms have many parameters that should be set by the user, they have not good color reduction results [2], [6]. Contrary to the claims of some above-mentioned references, lots of parameters and constant values selection for them with trial and error manner cannot be considered as the advantage of the method, and it may even be considered as a weakness of the method.

Also, the color reduction algorithms that are based on self-organizing map (SOM)artificial neural networks such as [3] and [4], due to a large amount of pixel data and the effect of data entry order, data size, and variety of training algorithms (with different training rate and timing), do not have high performance, especially for large size images.

The k-means algorithm has been used in many applications, including image color re-quantization [7], [9]. The main disadvantage of this algorithm is that the output depends on initial cluster centers and it usually converges to a local optimum. On the other hand, for large size images and a large number of clusters, it is time-consuming and produces unsatisfactory results. To improve the accuracy and speed of the algorithm (K-means), several scenarios have been presented for the selection of suitable cluster centers. Also, to increase the speed of the algorithm, pixels with duplicate colors have been removed and their effects have been applied as weights for unique pixels [10]. Although this method is suitable for images with a limited number of colors and it is time-consuming for large size images with a lot of colors. On the other hand, the problem of algorithm trapping in local optimums is still a concern. The k-means algorithm is trapped in local optimums for a low number of output colors (k clusters) in large size images and it is time-consuming for a lot of output colors. Also in this method [10], it is stated that the number of colors for ordinary images is about 5,000 colors, by examining datasets (even with small size 321×481), such as BSDS500, it becomes clear that roughly 70% of images contain more than 30,000 colors and even images with more than 80,000 colors exist. Also for images with a larger size, the number of colors increases sharply. On the other hand, the pre-processing that is done for color counting is also a process that takes a lot of time. The c-means based methods, which have been inspired by [10], have similar problems [5], [11].

Various algorithms have been introduced for adaptive re-quantization of color data in which the number of output colors is very low and in practice, these algorithms are suitable for image segmentation [12], [13].

Choosing more colors to maintain image quality, impose a lot of computational cost on these algorithms. In both methods of pixel color re-quantization and adaptive pixel color re-quantization; computational cost is heavily dependent on the image size and practically takes a lot of time for large size images. Similar methods for computational cost reduction that are based on removing duplicate colors and weighed clustering of unique colors, spend a lot of computational cost for a large size image with a lot of colors [5], [10], and [11].

Some recent works also performed image quantization by clustering on three-dimensional color data using swarm intelligence algorithms. Pérez-Delgado used the shuffled-frog leaping algorithm for image quantization [14]. This algorithm is applied to a subset of the original image pixels to reduce the execution time. She also used a combination of the Artificial Bee Colony Algorithm and the Ant-tree for color quantization [15]. Thompson et al. proposed a color clustering method using MacQueen's k-means algorithm, which comprises cluster center initialization to improve speed and quality of quantization [16]. Although in these works, the number of output colors is predefined and the computational cost is high and increases with image size.

To overcome this problem, some studies have a distinct look into the color space instead of the usual three-dimensional data clustering approach [17-21]. With this idea, instead of three-dimensional data clustering, the histogram of each color component with a maximum of 256 data can be clustered, and thus clustering computational cost will be independent of the image size. Of course, as it is known, the color reduction error in this method is higher than the three-dimensional data clustering methods and about high re-quantization error; these proposed algorithms are only used for a low number of output colors and image segmentation.

For each image with a relatively large amount of details, the perceived quality is no needs more than 5 bits for intensity resolution of each color component [1] and thus, considering 5 bit/channel (instead of 8 bit/channel) is sufficient to get proper color reduction results [22].

Also, a color reduction can be used as a preprocessing step in other image processing algorithms. Liu et al. used a mean shift clustering algorithm in local histograms of the image to improve color-texture segmentation results [23]. Potni et al. used an image quantization algorithm as a preprocessing step in color and texture feature extraction [24]. They showed that dimensions of feature vector can be reduced to 1/4, after performing image quantization, while the system accuracy is preserved or improved.

In this research, instead of three-dimensional data clustering, we follow an adaptive and independent re-quantization of each color component to a maximum of 32 bins. With this idea, instead of three-dimensional data clustering, adaptive binning of each color component histogram to a maximum of 32 bins can be done. Reducing 256 bins of each color component histogram to a maximum of 32 bins will be independent of image size. Also, due to the adaptive binning of each color component histogram and automatic determination of reduced bins, it is expected that the results of the method to be much better than usual clustering for each color component and be comparable with three-dimensional data clustering methods.

The rest of this paper is structured as follows. A new fast color reduction method based on the adaptive histogram bin merging approach is proposed in section II. Description of the image data sets, performance evaluation criteria, and description of experiments are described in Section III as an experimental setup. The research results are presented and discussed in section IV. Finally, the conclusion is given in section V and the references are given at the end of the paper.

II. PROPOSED METHOD

As mentioned in the previous section, clustering of pixel color data in three-dimensional color space provides good color reduction results but its high computational cost (especially in large-sized images with a lot of colors) is a major problem. In the first step to reduce this computational cost, it seems that color re-quantization can be done independently for each color component. This idea settles the problem of the high computational cost that extremely increases with the image size and number of output colors. Although the accuracy would be significantly reduced compared to the three-dimensional data clustering, Due to a large number of colors in three-dimensional space (up to 256×256×256), predetermining the reduced color number in this space is a more serious challenge relative to the one-dimensional color component or histogram bins (up to 256). Moreover, reduced colors are much more numerous than merged bins and their adaptive choice in the three-dimensional space requires more calculations. Accordingly, the proposed method is based on the adaptive bin merging of color components histograms.

Various supervised and unsupervised clustering methods have been developed based on meta-heuristic algorithms and swarm intelligence [8], [12], [13], [25-31] which provide good results. However, a high number of iterations and their computational cost are the two major disadvantages of these methods.

To reduce the number of GSA [32] iterations, the author has introduced the Planets And Black Holes GSA (PABH-GSA that is a modified version of GSA) [22]. Despite improving the GSA by changing its acceleration formula, reducing its control parameters, increasing its randomness, and optimizing its elitism (depending on the dimensions of the problem), PABH-GSA usage for color reduction is not yet satisfactory. Reducing the number of output colors to a maximum of 10 colors and resizing the image to 160 × 160, was including the limitations imposed on the method for its further reduction of computational cost. These limitations make the algorithm more suitable for segmentation than color reduction.

The block diagram of the new fast color reduction method based on the adaptive histogram bin merging approach is shown in fig 1.

The one-dimensional version of PABH-GSA with a newly defined cost function is developed to introduce an adaptive unsupervised method for bin merging of the color component histogram (with up to 256 different colors).

Proper reduction of bins strongly depends on the cost function definition for swarm intelligence algorithms. Neighbor bins must so merge that the bin merging error is not too high and the final merged bins (with a reasonable number) be relatively far from each other. Therefore, we defined a cost function based on the above objectives as the following formula.

$$BMCF = \frac{1}{ln(N_B)} \sum_{k=1}^{N_B} \frac{BMCF_k}{N_B}$$

$$BMCF_k = \begin{cases} \frac{BME_k}{B_{k+1}-B_k} & k = 1 \\ \frac{BME_k}{min(B_{k+1}-B_k, B_k-B_{k-1})} & k = 2, \ldots, N_B - 1 \\ \frac{BME_k}{B_k-B_{k-1}} & k = N_B \end{cases} \tag{1}$$

$$BME_k = \sqrt{\frac{\sum_{b_i \in B_k} N(b_i)|b_i - B_k|^2}{\sum_{b_i \in B_k} N(b_i)}}$$

In which N_B is the number of merged bins and B_k shows the $k\,th$ merged bin (1 to N_B), b_i shows $i\,th$ histogram bin (0 to 255) before merging. The $k\,th$ bin merging error and overall bin merging cost function is defined as BME_k and $BMCF$ respectively and $N(b_i)$ shows the $i\,th$ histogram's bin altitude.

The bin merging cost function $BMCF_k$ has a direct relationship with bin merging error of the $k\,th$ merged bin (BME_k) and a reverse relationship with the lowest distance from neighbors on both sides of the merged bins.

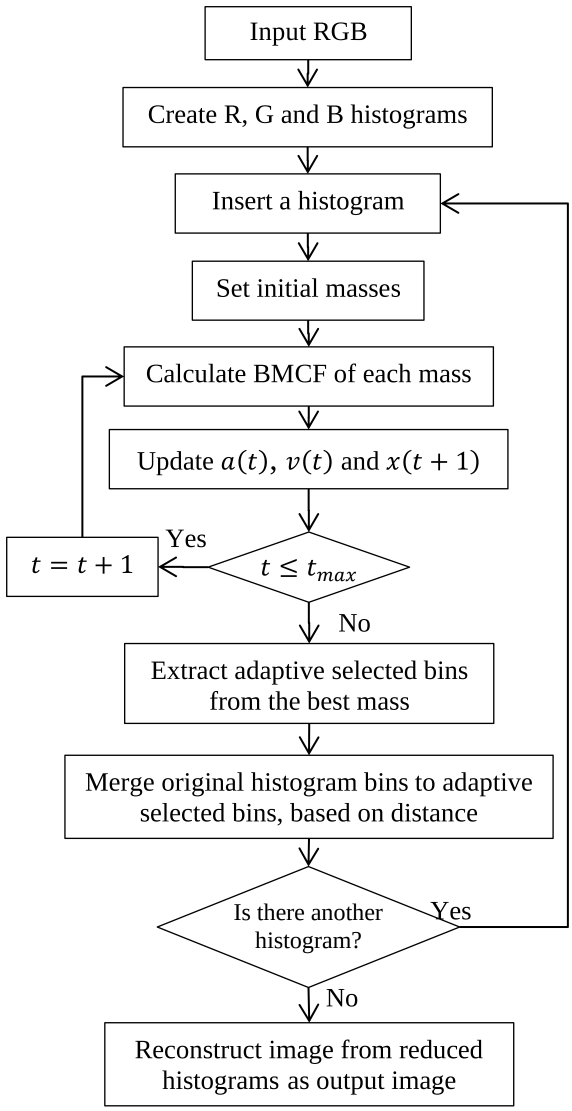

Fig. 1. Block diagram of the proposed color reduction method

A reasonable number of merged bins are also provided with $1/\ln(N_B)$ coefficient. For small values of N_B, this coefficient has a large range of variations but the range of changes is very small for big values. Since all calculations of this index are done in one dimension and only for 256 bins; the proposed index has a low computational cost.

In this paper, an unsupervised bin merging approach for each color component histogram has been considered as a simultaneous optimization of the number and location of merged bins. For this optimization, a fast and appropriate one-dimensional swarm optimization method is proposed using the PABH-GSA and the above-defined cost function.

The position of each particle in the search space involves some merged bins and some thresholds for verifying these merged bins that lead to a search space with $d + d$ dimensions. In this way, the particle structure is as follows.

$$x_i = [Th_1, Th_2, \dots, Th_d, B_1, B_2, \dots, B_d] \tag{2}$$

For threshold values greater than 0.5, the corresponding merged bin is considered, otherwise, it will be removed from the list of proposed merged bins of that particle. The number of 0.5 does not impose any condition on choosing or not choosing the merged bin and these two modes have equal odds. In each iteration, concerning threshold values, $BMCF$ (bin merging cost function) value is calculated for k selected merged bins ($2 \le k \le d$) of each particle. Finally, after the end of the whole iterations, the particle with the lowest cost simultaneously identifies the number and location of optimal merged bins. The modified equations are used to update the particle position.

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{3}$$

The velocity of particle displacement (for merged bins and threshold values) and the acceleration are obtained using equations 4 and 5 respectively.

$$v_i(t+1) = r_i(t) \times v_i(t) + a_i(t) \tag{4}$$

$$a_i(t) = e^{-\tau t} \sum_{j=1}^{n} r_i(t) \times M_j(t) \times sgn_{i,j}(t)$$
$$sgn_{i,j}(t) = \begin{cases} \frac{x_j(t)-x_i(t)}{|x_j(t)-x_i(t)|} & x_i(t) \ne x_j(t) \\ 0 & x_i(t) = x_j(t) \end{cases} \tag{5}$$

Where $x_i(t)$ and $a_i(t)$ are respectively the positions and accelerations applied to the $i\,th$ particle in the $t\,th$ iteration, τ is also a user-selectable coefficient (in the proposed range [0.1, 0.5]), $M_j(t)$ is the mass assigned to the $j\,th$ particle in the $t\,th$ iteration which is obtained from the following relations and r is a uniform random number in the range of zero and one $\left(r \sim U(0,1)\right)$.

$$M_j(t) = \frac{m_j(t)}{\sum_{j=1}^{Nm} m_j(t)}$$
$$m_j(t) = \frac{CF_j(t) - \min_j CF_j(t)}{\max_j CF_j(t) - \min_j CF_j(t)} \tag{6}$$

In which N_m is the number of selected masses for PABH-GSA that is considered to be 50 in the implementation. Some of the best masses are selected as black holes and their mass is updated by the following equation. In which β is also a user-selectable coefficient.

$$M_j(t) = \left(\beta \times r_j(t) + 1\right) M_j(t) \quad \textit{for } 20\% \textit{ of best masses} \tag{7}$$

During any iteration, according to the threshold values, the merged bins are selected, and then for each particle, the BMCF is calculated and finally, after the last iteration, the particle with the lowest cost determines the number and location of optimal merged bins.

In the proposed unsupervised bin merging method, the minimum and the maximum number of merged bins should be specified. In a general case, the minimum number of merged bins is usually equal to two bins and its maximum number can be empirically (optional) or according to limitations of the problem. In a particle, none of the threshold values (that have been randomly selected in the [0, 1] interval) may be greater than 0.5. In this case, at least two threshold values are selected randomly and again randomly initialized in the range of 0.5 to 1. In the cases where particle position exited from the acceptable interval, the boundary value will be replaced.

III. Experimental setup

A. Image datasets

Some of the most commonly used test images and databases (in the quantization literature) have been applied in the experiments. For demonstrating the PABH-GSA's performance, quantitative analysis is applied to the BSDS500 dataset and simultaneously qualitative evaluation of the proposed color reduction method is expressed for 12 images. The effectiveness of the proposed color reduction method compared to other recently developed methods is presented using the TID2013 dataset.

B. Performance evaluation criteria

To analyze the effectiveness of the proposed color reduction method, the color reduction efficiency and reduced color image quality was evaluated using our proposed Color Reduction Index (CRI) and recently introduced Directional Statistics based Color Similarity Index (DSCSI) [34] respectively. Color Similarity and Reduction Index (CSRI) have been considered as the overall efficiency of the color reduction method. DSCSI is computed in three steps: image transformation from the RGB into the spatial extension of CIELAB (S-CIELAB) color space, calculating the local features for the color similarity of hue, chroma, lightness and then obtaining the following six features: hue mean similarity, hue dispersion similarity, Chroma mean similarity, Chroma contrast similarity, lightness contrast similarity, lightness structural similarity and finally combining these six features into chromatic similarity (S_C) and achromatic similarity (S_A)

scores [34]. These two scores are directly used in the final DSCSI formula.

$$Q(I, I^*) = S_A (S_C)^\lambda \tag{8}$$

Where I and I^* are original and distorted images and λ is a weighting factor. Minor difference between the original and distorted image results in the DSCSI value be close to 1 [35].

Our proposed CRI only shows the relative difference in the number of colors between the original and reduced color images. This index is close to one if the number of colors in the reduced color image is much less than the number of colors in its original one.

$$CRI = 1 - \frac{number\ of\ reduced\ colors}{number\ of\ original\ colors} \tag{9}$$

CSRI is the product of two DSCSI and CRI indices (equation 10). For a significant color reduction which simultaneously leads to a qualitative visual image, the CSRI value is close to 1.

$$CSRI = DSCSI \times CRI \tag{10}$$

Looking at equation 10, it is clear that the proposed CSRI is developed based on the high similarity of the original and reduced color images (DSCSI close to one), despite the small number of colors in the reduced color image (CRI close to one).

C. Description of experiments

The first implementation is done to determine the maximum number of bins/channel. The second one was carried out to demonstrate PABH-GSA's performance. In the third implementation, the efficiency of the proposed adaptive color reduction method is shown visually and quantitatively for 12 selected images. Also, the efficiency of the proposed method is compared with some recently developed methods using 25 images in the TID2013 dataset.

The number of iterations in particle swarm optimization (PSO), GSA, and PABH-GSA is limited to 50. The C1 and C2 parameters in the PSO are considered equal 2 and the parameters α, G0, and T in GSA are selected equal 1, 1, and 50, respectively, and the parameters α and β in PABH-GSA are selected equal 0.02 and 0.5. For the weighted k-means algorithm, the number of iterations equal to 100 and the optimal number of bins that have been obtained by PABH-GSA, is considered as the number of clusters.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. Maximum number of bit per channel

The main goal of the proposed color reduction method is to reduce the number of bits that are needed for each color component so that the visual quality of the image is maintained and color reduction indices will be within the acceptable range. The effect of the maximum selected bits in each color component is shown for DSCSI, CRI, and CSRI indices. As you can see in fig. 2 and fig. 3, reducing the number of bits to seven bits per component does not lead to a proper color reduction. Also, reducing the number of bits to less than four bits causes a sharp decrease in the visual index. Altogether, reducing the number of bits to five bits, leads to suitable results, in terms of visual index and color reduction index for images with a uniform background as well as images with busy backgrounds.

B. The efficiency of PABH-GSA based intelligent histogram binning

The proposed method was implemented for the BSDS500 dataset with the constraint of a maximum of five bits in each color component and indices results are shown in Table 1. It should be noted that the number of classes in the weighted k-means method is equal to the number of obtained bins by the adaptive method. The weighted k-means is a supervised algorithm and cannot select the optimal number of bins. Despite the weighted k-means use the optimal number of bins obtained by the PABH-GSA, the PABH-GSA results are better than the weighted k-means ones.

As shown in Table 1, adaptive histogram binning with PABH-GSA has the best performance. Because, for the visual index, the highest average value with the lowest standard deviation has been obtained, and also Image quality index has appropriate values (more than 0.93).

C. Performance evaluation and comparison

The effectiveness of the adaptive color reduction method is shown visually in fig. 4 and related indices values are seen in Table 2 (for 12 selected images of the BSDS500 dataset). The runtime of the proposed color reduction method for the different resolutions of a large size image is shown in Table 3. Computational cost in the pixel data clustering and histogram binning approach is compared in Table 4. Our method is also compared with the existing methods in Table 5 (for 25 images of the TID2013 dataset).

As shown in Table 2, the proposed method (PABH-GSA) has much better performance than the other methods in terms of DSCSI and also has good CRI values. Although the PSO algorithm has led to better CRI values, its DSCSI values, compared to the proposed method, do not show good performance in all of the images (especially in images 35058, 35070, and 134008). Excessive reduction in the number of bits and thus CRI increment results in sharp reduction at the output image quality and other words a sharp drop in DSCSI value. The proposed bin merging cost function (BMCF) has been defined to reduce the difference between the output image and the original image. This means that the proposed adaptive algorithm should directly lead to a high DSCSI value and implicitly a suitable CRI value. Accordingly, the overall performance of the proposed algorithm for color reduction and image quality preservation is better in terms of CSRI.

The proposed color reduction method adaptively reduces the number of bins from 256 to a maximum of 32 bins for each color component histogram and the runtime of the method is independent of image size. To investigate this advantage, the proposed method was implemented on different sizes of a high-resolution image (fig. 5) and runtimes were compared with each other (Table 3).

As shown in Table 3, the runtime for the original image is almost the same as other reduced-size images. Also, despite the sharp drop in color content, the color reduction result for the high-resolution image has satisfactory visual quality. The minor runtime changes are due to the runtime changes of the swarm algorithm (in different runs), histogram calculation, and regenerating the reduced color image from newly merged bins. Of course, it should be noted that our non-optimized code, has been run on an ordinary computer with MATLAB software to only compare runtimes for images with different sizes.

To compare computational cost in pixel data clustering and histogram binning approach, consider an image from the BSDS500 with a size of 321×481 that has resulted in 1000 colors after histogram binning. The number of data and required calculations for distance and variance at each particle in any iteration has illustrated in Table 4. Each data should belong to a cluster that has a minimum distance. Therefore, it is necessary to calculate the distances between all data and all cluster centers. To evaluate the clustering result, the mean of intra-cluster variances is also calculated by the cost function. In a special state, it has been considered that all clusters have equal data numbers. As shown in Table 4, the proposed method has a few numbers of data that is independent of the image size, and all calculation is done in one-dimensional space. But pixel data clustering has a large number of data that is dependent on the image size and all calculation is done in the three-dimensional space. Therefore, the proposed method with fewer calculations is very faster than pixel data clustering and for larger images, this difference is very higher. Results of the proposed method and pixel data clustering methods for the TID2013 dataset are compared in Table 5. According to the results shown in Tables 3 and 5, despite the low computational cost and its independence of image size, the proposed method has led to good indices values, so that the visual difference of the images is not so noticeable.

232038

105053

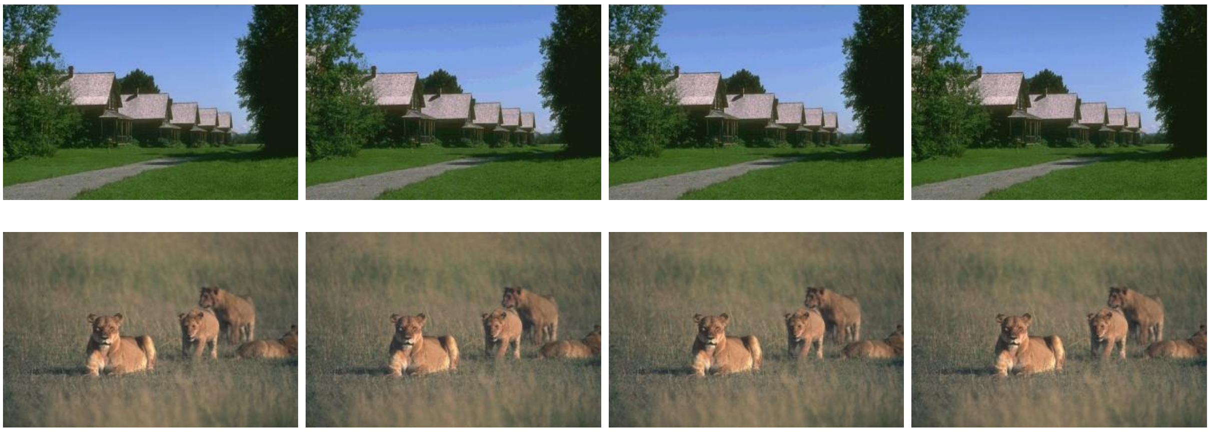

Fig. 2. Effect of maximum selected bins on the visual appearance of images 232038 (above) and 105053 (below) in BSDS500 dataset, from left to right: original image, maximum selected bins is 16, 32 and 64

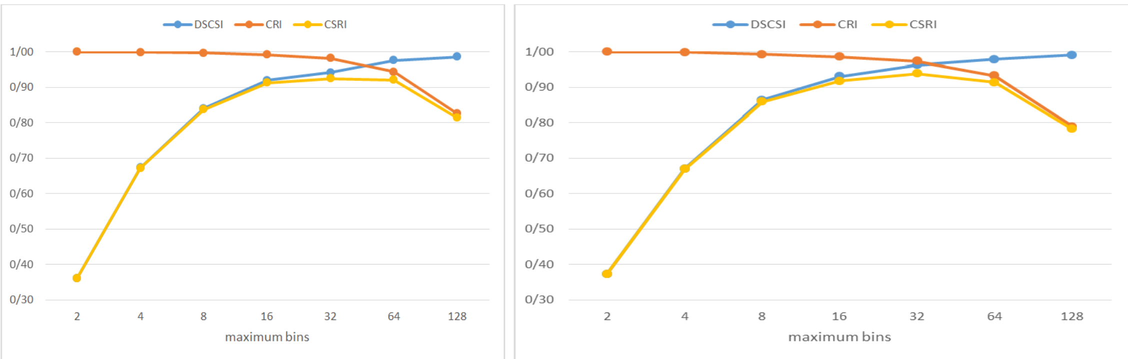

Fig. 3. Effect of maximum selected bins on the DSCSI, CRI, and CSRI indices for image 232038 (left) and 105053 (right) in the BSDS500 dataset

TABLE 1

COMPARING MEAN AND STANDARD DEVIATION (STD) OF INDEXES FOR 500 IMAGES IN THE BSDS500 DATABASE (VALUES ARE AVERAGED FOR FIVE INDEPENDENT RUNS OF EACH ALGORITHM)

	PSO		GSA		k-means		PABH-GSA	
	mean	STD	mean	STD	mean	STD	mean	STD
DSCSI	0.918	0.058	0.902	0.043	0.926	0.039	**0.947**	**0.028**
CRI	**0.987**	**0.006**	0.981	0.009	0.981	0.008	0.98	0.008
CSRI	0.906	0.057	0.885	0.042	0.908	0.039	**0.928**	**0.029**

Fig. 4. From left to right, original images, results of PSO, GSA, K-means, and PABH-GSA

TABLE 2
COLOR REDUCTION RESULTS FOR 12 IMAGES

image	original colors	index	PSO	GSA	k-means	PABH-GSA
3063	15618	DSCSI	0.9226	0.8929	0.9119	**0.9315**
		CRI	**0.978**	0.9674	0.9719	0.9732
		CSRI	0.9023	0.8638	0.8863	**0.9065**
12003	71166	DSCSI	0.9484	0.9424	0.9547	**0.9561**
		CRI	0.9756	0.9777	0.9738	**0.9802**
		CSRI	0.9253	0.9214	0.9297	**0.9372**
12074	45298	DSCSI	0.9226	0.8551	0.8587	**0.9439**
		CRI	**0.9853**	0.9759	0.9705	0.9789
		CSRI	0.9091	0.8345	0.8334	**0.924**
35058	26995	DSCSI	0.8668	0.8949	0.9258	**0.9489**
		CRI	**0.9875**	0.9847	0.9746	0.97
		CSRI	0.856	0.8813	0.9023	**0.9204**
35070	38802	DSCSI	0.8539	0.8542	0.8452	**0.926**
		CRI	**0.9945**	0.9793	0.9824	0.9788
		CSRI	0.8492	0.8365	0.8303	**0.9063**
100075	40817	DSCSI	0.9488	0.9332	0.9689	**0.98**
		CRI	**0.9862**	0.9819	0.985	0.981
		CSRI	0.9357	0.9163	0.9543	**0.9614**
105053	17659	DSCSI	0.9269	0.9372	0.8675	**0.9598**
		CRI	**0.9854**	0.9702	0.9827	0.9752
		CSRI	0.9134	0.9093	0.8525	**0.936**
124084	42280	DSCSI	0.9052	0.8738	0.9306	**0.9435**
		CRI	**0.9785**	0.9714	0.9647	0.9663
		CSRI	0.8857	0.8488	0.8977	**0.9118**
134008	13441	DSCSI	0.8766	0.9524	0.9621	**0.9679**
		CRI	**0.9932**	0.9763	0.9887	0.9862
		CSRI	0.8706	0.9298	0.9513	**0.9545**
231015	68360	DSCSI	0.9557	0.9346	0.9324	**0.9599**
		CRI	0.9895	0.9853	**0.9908**	0.9903
		CSRI	0.9456	0.9208	0.9238	**0.9506**
232038	31053	DSCSI	0.9	0.9328	0.9094	**0.9351**
		CRI	**0.9835**	0.9834	0.9824	0.9809
		CSRI	0.8852	**0.9174**	0.8935	**0.9172**
253027	26548	DSCSI	0.9306	0.94	0.8817	**0.9526**
		CRI	**0.9924**	0.9874	**0.9924**	0.9907
		CSRI	0.9235	0.9281	0.875	**0.9437**

(a)

(b)

Fig. 5.A high-resolution image with 350851 colors (a) and its reduced color image with 3334 colors (b)

TABLE 3
RESULTS FOR DIFFERENT SIZES OF AN IMAGE

Image	Image size	Number of pixels	Original colors	Reduced colors	DSCSI	CRI	CSRI	Time(Sec)
k05	2048×3072	6291456	350851	3334	0.9325	0.9905	0.9236	5.7527
	1024×1536	1572864	369911	3078	0.9310	0.9917	0.9233	5.4694
	512×768	393216	167011	1882	0.9476	0.9887	0.9369	5.3664
	256×384	98304	64083	1852	0.9792	0.9711	0.9509	5.1791
	128×192	24576	20616	1280	0.9817	0.9379	0.9207	5.2803

TABLE 4
THE NUMBER OF NEEDED CALCULATIONS TO DETERMINE THE DATA DISTANCE WITH THE CLUSTER CENTERS AND THE INTRA-CLUSTER VARIANCES IN EACH ITERATION AND FOR EACH PARTICLE

	Pixel data clustering	histogram binning
number of data	Pixels = 481×321	**256**
number of centers	1000	3×32 = **96**
The average number of data in each class	Pixels /1000 ≈ 154	256/32 = **8**
number of distance calculations	1000×Pixels = 154,401,000	256×32×3 = **24,576**
number of variance calculations	1000 with 154 data	**96** with **8** data

TABLE 5
THE PROPOSED HISTOGRAM BINNING BASED METHOD COMPARED SOME METHODS WITH THE REPORTED RESULTS IN THE REFERENCE [30]

	POP	MCut	Oct	NeuQuant	Wu	POP+KM	MCut+KM	Wu+KM	bin merging
DSCSI	0.875	0.9378	0.9408	0.9136	**0.9681**	**0.9622**	**0.9631**	**0.9712**	**0.9609**
CRI	0.9804	0.9804	0.9804	0.9804	0.9804	0.9804	0.9804	0.9804	0.9625
CSRI	0.8578	0.9194	0.9223	0.8957	**0.9491**	**0.9433**	**0.9442**	**0.9521**	**0.9249**

In the proposed method, the pixel depth decreases, but clustering methods do not necessarily lead to a decrease in pixel depth. Also, the number of bins in the proposed method and therefore the number of colors in the output image is calculated with an adaptive approach. However, in clustering methods, the number of colors should be determined by the user.

V. CONCLUSIONS

In this paper, a new adaptive color reduction method is presented which is independent of image size. This method is based on the adaptive histogram binning of each color component. As regards that each histogram has a maximum of 256 bins and adaptive reduction of this number for a swarm algorithm is not very time-consuming, the proposed method has less computational cost compared to other existing methods. Additionally, in existing intelligent approaches for color reduction, the total number of colors is predefined by the user, and the color reduction does not necessarily lead to a decrement in pixel depth. A fixed number of output colors do not lead to a good color reduction in different images. Some images need more colors and some others need less number of colors. However, in the proposed method, the maximum number of colors for each component is limited so that the pixel depth is reduced and the number and position of histogram bins (the number of bins and their centers) are adaptively obtained by the color content of the related component.

In the proposed adaptive intelligent image color reduction approach, the number of output colors is selected automatically and adaptively by the algorithm considering the color content of the input image. Also, existing studies used 3D data clustering algorithms, which have high computational costs, especially for large size images. In fact, in existing methods, the number of data which are clustered is equal to the number of pixels in the image. However, in the proposed method, R, G, and B histograms are clustered, which have a fixed number of data for different sizes of the input image.

Simulation results showed proper performance of the proposed method for color histogram binning that leads to a significant color reduction of each component and results in a sharp decrease in the number of overall colors in such a way that preserves the visual quality of the image.

Due to pixel depth reduction and no need for manual adjustment of parameters, this algorithm can be considered as a hardware-friendly algorithm. Also due to the sharp decrease in color data, the algorithm can be used as a preprocessing step for other computer vision algorithms. For example, input images with fewer color data can be led to faster training and better results in Convolutional Neural Network (CNN).

In some applications such as image segmentation and edge detection, removing extra data will help to get more accurate results. Also, because of the low computational cost (especially for large size images), image segmentation should be done in two steps: at the first, the number of colors can be significantly reduced, and then, image segmentation can be performed by fewer color data and more degree of freedom.

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روش سریع کاهش رنگ تصاویر مبتنی بر رویکرد بین‌بندی تطبیقی هیستوگرام

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چکیده- اکثر روش‌های کاهش رنگ در تصاویر که مبتنی بر خوشه‌بندی تصویر در یک فضای رنگی سه بعدی، هزینه‌های محاسباتی بسیار بالایی به خصوص برای تصاویر در اندازه‌های بزرگ دارند. در این مقاله یک روش جدید تطبیقی برای کاهش سریع رنگ ارائه شده است که از نظر محاسباتی مستقل از اندازه تصویر است و عمق پیکسل را از ۲۴ بیت (که برای نشان دادن مقادیر سه‌گانه رنگ در اغلب مدلهای RGB سخت افزار محور استفاده می‌شود) به حداکثر ۱۵ بیت کاهش می‌دهد. برای دستیابی به این هدف با معرفی یک تابع هزینه ترکیبی جدید و با استفاده نسخه اصلاح شده GSA (که PABH-GSA نامیده می شود)، یک رویکرد بین‌بندی تطبیقی هیستوگرام ایجاد شده است. هرچند دقت بازرقومی‌سازی مکعب رنگ در رویکرد بین‌بندی هیستوگرام در مقایسه با روش خوشه‌بندی داده‌های سه بعدی کمتر است، اما کاهش قابل توجهی هزینه محاسباتی را به دنبال دارد. در این مقاله ضمن استفاده از این مزیت به دنبال کاهش خطای بازرقومی‌سازی با استفاده از بین‌بندی تطبیقی مولفه‌های رنگ RGB هستیم. علیرغم کاهش قابل توجه در عمق پیکسل، رویکرد کاهش رنگ پیشنهادی، به دلیل کاهش تطبیقی رنگ تصاویر، منجر به کاهش رنگ مناسب برای طیف گسترده ای از تصاویر می‌شود.

واژه‌های کلیدی: هوش جمعی، الگوریتم جستجوی گرانشی، کاهش رنگ، بین‌بندی تطبیقی هیستوگرام.