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A fast MPEG-7 dominant color extraction with new similarity measure for image retrieval

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Abstract

Dominant color descriptor (DCD) is one of the color descriptors proposed by MPEG-7 that has been extensively used for image retrieval. Among the color descriptors, DCD describes the salient color distributions in an image or a region of interest. DCD provides an effective, compact, and intuitive representation of colors presented in an image. In this paper, we will develop an efficient scheme for dominant color extraction. This approach significantly improves the efficiency of computation for dominant color extraction. In addition, we propose a modification for the MPEG-7 dissimilarity measure, which effectively improves the accuracy of perceptive similarity. Experimental results show that the proposed method achieves performance improvement not only in saving features extraction cost but also perceptually similar image retrieval.

Keywords: Dominant color descriptor; Color quantization; Dissimilarity measure; MPEG-7

1. Introduction

Nowadays, color images are extensively used in multimedia applications. The use of low-level visual features to retrieve relevant information from image and video databases has received much attention in recent years. In general, color is one of the most dominant and distinguishable visual features. In the current version of the MPEG-7 Final Committee Draft, several color descriptors have been approved including number of histogram descriptors and a dominant color descriptor (DCD) [1,3].

MPEG-7 specifies seven color descriptors [1]. It includes dominant colors, scalable color histogram, color structure, color layout, and GoF/GoP color. In [15], the authors have shown that the early perception in human visual system performs dominant color identification, and eliminates the fine details and colors in small areas. Therefore, for macroscopic level, human perceive images as a combination of dominant colors no matter how the exact color distribution. In MPEG-7, DCD provides an effective, compact, and intuitive salient color representation, and describe the color distribution in an image or a region of interesting [1]. This feature descriptor contains two main components: (1) representative colors and (2) the percentage of each color. In [2], a quadratic-like measure of histogram distance was proposed for DCD dissimilarity measure. In this paper, we will develop an effective color extraction scheme, and improve similarity measure for DCD.

In order to extract the representative colors, some efforts have focused on the color extraction by clustering methods [2–6]. In [15], the dominant colors were extracted by following steps: (1) codebook design; (2) color quantization by clustering; (3) speckle noise removal and remapping procedures; (4) the representative dominant colors of quantization image are selected by available codebook. However, to develop a universal codebook that suit for various nature image database is a very challenging problem. Furthermore, for color quantization, the generalized

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Lloyd algorithm (GLA) [7] is commonly used for clustering. However, there are some drawbacks in GLA. True type color images consist of more than 16 million (2^{24}) different colors in a 24 bit full RGB color space; therefore, the conventional clustering algorithms are very time consuming. Moreover, it is difficult to obtain global optimal. In GLA, the number of clusters must be predetermined, and the initial seeds may be different due to different approaches. This will cause the number of dominant colors of an image to vary because different parameter settings. Moreover, it requires large amounts of computation. Finally, in GLA, the representative colors depend on the color distribution; therefore, the greater part of representative colors will be located in the higher color distribution range with smaller color distance. It is may be not consistent with human perception because human eyes cannot exactly distinguish the colors with close distance. Therefore, in this paper, we will develop an efficient dominant color extraction scheme to address these problems.

On the other hand, we have found that there is a drawback on the quadratic-like measure of histogram distance [1,2] for dominant color descriptor in which the dissimilarity between the query image and target image is calculated. In our works, we will illustrate several artificial and real image examples to show that this dissimilarity measure does not match the human perception under some conditions. It may result in incorrect ranks among images with similar salient color distribution. It is only quite recently that Po and Wong [8] have proposed a new palette histogram similarity measure to solve this problem. In our work, we will propose a more effective scheme to improve the accuracy of similarity measure, we also investigate several similarity measure methods [14,16] and compare their performance to demonstrate the effectiveness of the new scheme.

In this paper, we propose a fast scheme to extract the representative colors. It will be shown that the proposed method reduces computation cost, and gives good clustering results which are truly suitable for the applications of image retrieving. On the other hand, we introduce a modification in the dissimilarity measure for measuring the similarity. The new method can improve the accuracy and performance of retrieval. In the experimental results, compared to MPEG-7 and palette histogram similarity measure [8], our proposed approach achieves ARR improvement rates of 4.2% and 6.6%; and ANMRR improvement rates of 5.4% and 4.8%, respectively. In summary, we will propose a more effective DCD scheme that improves not only the accuracy of similarity measure but also efficiency of representative color extraction.

The paper is organized as follows: the color quantization for extracting the feature is explained in Section 2. Similarity measure method is introduced in Section 3. Discussions and comparisons are made in Section 4. Finally, a short conclusion is presented in Section 5.

2. Fast color quantization

In order to extract the dominant colors from an image, a color quantization algorithm has to be predetermined. It is very common to use the modified generalized Lloyd algorithm or fast color quantization algorithm with clusters merging; and then a small number of representative colors and their percentages of an image can be obtained. The dominant color descriptor in MPEG-7 is defined as

$$F = \{\{c_i, p_i\},\ i = 1, \ldots, N\}, \tag{1}$$

where N is the total number of dominant colors for an image, c_i is a 3-D dominant color vector, p_i is the percentage for each dominant color, and the sum of p_i is equal to 1.

The GLA is the most widely used algorithm to extract dominant colors from an image; however, it needs expensive computation cost. Furthermore, there are several intrinsic problems associated with the existing algorithm as follows.

1. It may give quite different kinds of clusters when cluster number is changed.
2. A correct initialization of the cluster centroid is a crucial issue because some clusters may be empty if their initial centers lie far from the distribution of data.
3. The effectiveness of the GLA depends on the definition of "distance"; therefore, different initial parameters of an image may cause different clustering results.

Moreover, the idea behind the GLA is also not suitable for dominant colors extraction. Because the color extraction using GLA is the same as color quantization, which the representative colors are obtained by minimizing the distortion (i.e., quantization error). In order to reduce the distortion, in GLA, the representative colors will depend on the color distribution; therefore, the greater part of representative colors will locate in the higher color distribution range with smaller color distance. Based on aforementioned observation, we believe that the GLA is not a good choice for dominant color extraction in general. Using the splitting algorithms is a possible way to overcome the difficulties [9–12]. Since the algorithms start with arbitrary random centroids, they do not need initial conditions. However, the algorithms often converge to local optimal and usually require high computational complexity. It can be concluded that there is no ideal algorithm for extracting dominant colors.

According to our extensive experiments, the selection of color space is not a critical issue for DCD extraction. Therefore, for simplicity and without loss of generality, we use RGB color space in our work. Besides, there is no strong dependence between the number of seeds and the extracted dominant colors. In other words, expensive algorithms did not induce significant improvement for dominant color extraction. Therefore, a simple but fast approach is adequate to solve this problem at this stage. The proposed approach is based on the idea that if we can develop a simple rule which does not initial seeds in [7] or possible choices of parameters setting in [15] to quantize and cluster the colors, then the same result of dominant color extraction can be obtained for different database providers. This can effectively improve the performance and consistency for real applications.

According to the quantity of each color component, the RGB color space is uniformly divided into 8 coarse partitions as shown in Fig. 1. If there are several colors located on the same partitioned block, they are assumed to be similar. The reasons for this assumption are described as follows. First, we have to extract 3–8 dominant colors [1] on average from 16 million (2^{24}) different colors to represent an image or a region; therefore, a simple and effective method for color reduction is desired. Second, the coarse quantization should be able to separate two different color distributions far enough; and it will not produce multiple representative colors with close distance. Although the GLA effectively reduces the quantization distortion; however, the detailed quantization would partition the similar color into different representative colors. It is not consistent with human perception because human eyes cannot exactly distinguish the colors with close distance. On the contrary, in LBA, the quantization results should have enough distinctive attribute so that it is more consistent with human perception, even though the quantization error is larger than GLA. The detailed comparisons and numerical analyses will be given in Section 4.1

In our work, the dominant colors are extracted as an agglomerative result of adjacent partitions of the color clusters with our merging algorithm. The detailed algorithm is explained as follows.

After the coarse partition step, the centroid of each partition ("*colorBin*" in MPEG-7) is selected as its quantized color. Let $\mathbf{x} = (x^{R}, x^{G}, x^{B})$ represents color components of a pixel with color components red, green, and blue, respectively, and c_i be the quantized color for partition i. The average value of color distribution for each partition center can be calculated by

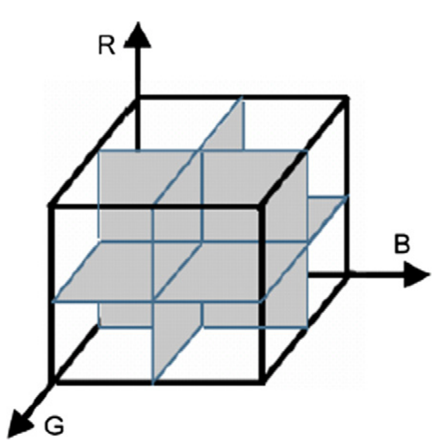


Fig. 1. The coarse division of RGB color space.

$$\bar{\mathbf{x}}_i = \frac{\sum_{\mathbf{x}\in c_i}\mathbf{x}}{\sum_{\mathbf{x}\in c_i} 1}. \tag{2}$$

After the average values are obtained, each quantized color $c_i = (\bar{\mathbf{x}}_i^{R}, \bar{\mathbf{x}}_i^{G}, \bar{\mathbf{x}}_i^{B}),\ 1 \leqslant i \leqslant 8$ can be determined. Consequently, we calculate mutual distance of two adjacent c_i, and then merge similar "*colorBins*" using weighted average agglomerative procedure in the following equation.

$$\begin{aligned}
x^{R} &= x_1^{R} \times \left(\frac{p_{R,1}}{p_{R,1}+p_{R,2}}\right) + x_2^{R} \times \left(\frac{p_{R,2}}{p_{R,1}+p_{R,2}}\right),\\
x^{G} &= x_1^{G} \times \left(\frac{p_{G,1}}{p_{G,1}+p_{G,2}}\right) + x_2^{G} \times \left(\frac{p_{G,2}}{p_{G,1}+p_{G,2}}\right),\\
x^{B} &= x_1^{B} \times \left(\frac{p_{B,1}}{p_{B,1}+P_{B,2}}\right) + x_2^{B} \times \left(\frac{p_{B,2}}{p_{B,1}+p_{B,2}}\right).
\end{aligned} \tag{3}$$

In Eq. (3), p_R, p_G, and p_B represent the percentages in R, G, and B components, respectively. The merge processes are iterated until the minimum Euclidian distance between the adjacent color cluster centers being larger than the threshold. In [13], it is suggested that T_d can be 10–15. Because the dominant colors should be significant enough, therefore we will merge the insignificant color into the its neighbouring color. We check each survived color, if its percentage is less than threshold T_m, it will merge into the nearest color. In our work, we set the T_m as 6%. As a result, we obtain a set of dominant colors, and the final number of dominant colors is constrained to 4–5 on average. In the following, we call the proposed method as linear block algorithm (LBA) for simplicity. It will be demonstrated in Section 4.1 that the LBA achieves more satisfactory results than that of the GLA algorithm.

3. Similarity measure

In [2], a quadratic-like measure of histogram distance was introduced for dissimilarity measure of this descriptor. However, DCD similarity matching does not fit human perception very well, and it will cause incorrect ranks for images with similar color distribution [8]. Based on our observation, we found that similarity measure depends on both the number of dominant colors and their percentages.

In the following, we will explain the reason about the poor results, and then introduce a modification on distance function to improve the robustness of similarity measure. Consider two color features $F_1 = \{\{c_i, p_i\},\ i = 1, \ldots, N_1\}$ and $F_2 = \{\{b_j, q_j\},\ j = 1, \ldots, N_2\}$. In order to determine the similarity score, the quadratic-like dissimilarity measure [1,2] between two images F_1 and F_2 is calculated by

$$D^2(F_1, F_2) = \sum_{i=1}^{N_1} p_i^2 + \sum_{j=1}^{N_2} q_j^2 - \sum_{i=1}^{N_1}\sum_{j=1}^{N_2} 2a_{i,j}\, p_i q_j, \tag{4}$$

where $a_{i,j}$ is the similarity coefficient between color clusters c_i and b_j.

The similarity coefficient is given by

$$a_{i,j} = \begin{cases} 1 - d_{i,j}/d_{\max} & d_{i,j} \leqslant T_d \\ 0 & d_{i,j} > T_d \end{cases}, \quad (5)$$

where $d_{i,j}$ is Euclidean distance between two color clusters c_i and b_j

$$d_{i,j} = \|c_i - b_j\|. \quad (6)$$

The threshold T_d is the maximum distance used to judge whether two color clusters are similar, and $d_{\max} = \alpha T_d$. Notation α is a parameter. Let $\alpha = 1$, and consider the case when the Euclidean distance of two color clusters is slightly smaller than maximum distance. From Eq. (5), the similarity coefficient $a_{i,j}$ between the two color clusters will be very close to zero; therefore, it cannot clearly distinguish between the colors exceeding the maximum distance. In order to properly reflect similarity coefficient between two color clusters, the parameter α is set to 2 and $T_d = 25$ in this work.

From our experiments, we noticed that the quadratic-like measure of histogram distance on the right-hand side of Eq. (4) may incorrectly reflect the distance between two images. The improper results are mainly caused by two reasons: (1) If the number of dominant colors for target image increases, it may causes incorrect result. (2) If one dominant color can be found both in target images and query image, then a high percentage of the color in target image might cause improper result. In the following, we will present two artificially examples to explain it. For the first example, consider a query image Q and two target images F_1 and F_2 as shown in Fig. 2. In Fig. 2(a), the percentage values for each dominant color of Q are 0.6, 0.25, and 0.15, respectively. Similarly, the percentage values of F_1 and F_2 are labeled in Fig. 2(b) and (c). These color features are described as follows:

$$Q = \{(q_1, 0.6), (q_2, 0.25), (q_3, 0.15)\},$$
$$F_1 = \{(t_{11}, 0.3), (t_{12}, 0.2), (t_{13}, 0.15), (t_{14}, 0.15), (t_{15}, 0.1), (t_{16}, 0.1)\},$$
$$F_2 = \{(t_{21}, 0.6), (t_{22}, 0.25), (t_{23}, 0.15)\},$$

where the first component in the parenthesis is dominant color, and the second component is its percentage. For simplicity, we assume that the colors in query image Q and the colors in the target images F_1 are all different and exceed the threshold T_d, thus the similarity coefficients $a_{i,j}$ that define in Eq. (5) are all zero. On the contrary, there are two dominant colors in Q same as target image F_2, i.e., $q_2 = t_{22}$ and $q_3 = t_{23}$. Obviously, from human perception, the query image is more similar to Fig. 2(c) than to Fig. 2(b). However, we calculate the dissimilarity using Eq. (4) as

$$\begin{aligned} D^2(Q, F_1) &= (0.6^2 + 0.25^2 + 0.15^2) + (0.3^2 + 0.2^2 + 0.15^2 \\ &\quad + 0.15^2 + 0.1^2 + 0.1^2) - 0 \\ &= 0.64 \end{aligned}$$

and

$$\begin{aligned} D^2(Q, F_2) &= (0.6^2 + 0.25^2 + 0.15^2) + (0.6^2 + 0.25^2 + 0.15^2) \\ &\quad - 2 \times 1(0.25 \times 0.25 + 0.15 \times 0.15) \\ &= 0.72. \end{aligned}$$

The results indicate that the query image is more similar to Fig. 2(b) than to Fig. 2(c). Apparently, the results are not consistent with human perception.

Moreover, if we change the condition of above example slightly; assume that there is none similar color between query image Q and two target images F_1 and F_2. Theoretically, we expect that $D^2(Q, F_2)$ should be equal to $D^2(Q, F_1)$. However, the quadratic-like measure is calculated as

$$\begin{aligned} D^2(Q, F_1) &= (0.6^2 + 0.25^2 + 0.15^2) + (0.3^2 + 0.2^2 \\ &\quad + 0.15^2 + 0.15^2 + 0.1^2 + 0.1^2) \\ &= 0.64 \end{aligned}$$

and

$$\begin{aligned} D^2(Q, F_2) &= (0.6^2 + 0.25^2 + 0.15^2) \\ &\quad + (0.6^2 + 0.25^2 + 0.15^2) \\ &= 0.89. \end{aligned}$$

As it can be observed in Eq. (4), the quadratic-like measure is determined by two positive squared terms and

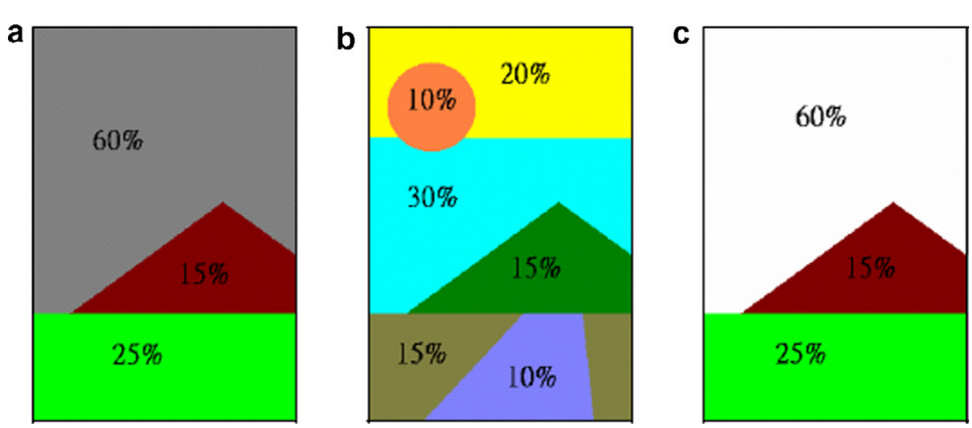


Fig. 2. Artificial image with the dominant colors and their percentage values for example 1: (a) a query image Q, (b) target images F_1, and (c) target image F_2.

one negative term in the distance function. If there is no similar color between two images, then the distance function is determined by the number of dominant colors for query and target image, respectively. In this case, if the number of dominant colors for target image increases, the sum of the square terms will have a strong tendency to decrease its value, and then causes improper matching. Therefore, we can conclude that the dissimilarity between two images strongly depends on the number of dominant colors.

In the second example, we will demonstrate that if one dominant color can be found both in target images and query image, then a high percentage of the color in target image might cause improper result. Consider the same artificially query image Q in first example and two target images F_1 and F_2 which both contain four dominant colors are shown in Fig. 3(b) and (c), respectively. These color features are described as follows:

$$Q = \{(q_1, 0.6), (q_2, 0.25), (q_3, 0.15)\},$$
$$F_1 = \{(t_{11}, 0.35), (t_{12}, 0.35), (t_{13}, 0.15), (t_{14}, 0.15)\},$$
$$F_2 = \{(t_{21}, 0.5), (t_{22}, 0.25), (t_{23}, 0.15), (t_{24}, 0.1)\}.$$

Assume that $q_2 = t_{11} = t_{22}$, $q_3 = t_{23}$, and all the other colors in Q, F_1 and F_2 are different and exceed the threshold T_d. That is, target images F_1 contains only one color which can be found in query image Q, and target images F_2 contains two similar colors. Moreover, the sum of percentage values of similar dominant colors between Q and F_2 is larger than that of F_1 ($40\% > 35\%$). Intuitively, the query image is more similar to F_2 than to F_1. However, applying Eq. (4) to calculate the dissimilarity, we have

$$\begin{aligned} D^2(Q,F_1) &= (0.6^2 + 0.25^2 + 0.15^2) + (0.35^2 + 0.35^2 \\ &\quad + 0.15^2 + 0.15^2) - (2 \times 1 \times 0.25 \times 0.35) \\ &= 0.445 + 0.29 - 0.175 \\ &= 0.56 \end{aligned}$$

and

$$\begin{aligned} D^2(Q,F_2) &= (0.6^2 + 0.25^2 + 0.15^2) + (0.5^2 + 0.25^2 + 0.15^2 \\ &\quad + 0.1^2) - 2 \times 1 \times (0.25 \times 0.25 + 0.15 \times 0.15) \\ &= 0.445 + 0.345 - 0.17 \\ &= 0.62. \end{aligned}$$

In this example, we may observe that the number of dominant colors in target images F_1 and F_2 are the same, and we can reason out that $D^2(Q,F_2) > D^2(Q,F_1)$ is mainly caused by the negative term in the distance function. The results reveal that the query image is more similar to Fig. 3(b) than Fig. 3(c). Again, the results are not consistent with human perception. The above two crafted examples imply that the definition of the distance in Eq. (4) should be a function that depends not only on the percentages of dominant colors but also the number of dominant colors. In general, an increase in the number of dominant colors leads to decrease the distance between two images. Furthermore, if there exist one similar color in the target image with large percentage, it has strong tendency to decrease the distance no matter what the color percentage in the query image.

Previously proposed color distance measures fail to fully capture both factors. In [14], Ma et al. defined a similarity measure which is a product of percentage difference and distance in RGB color space, i.e.,

$$D(c_i, c_j) = |p_i - p_j| \times \sqrt{(c_i^R - c_j^R)^2 + (c_i^G - c_j^G)^2 + (c_i^B - c_j^B)^2}, \quad (7)$$

however, when either component is very small the remaining component becomes irrelevant [16]. In addition, in an extreme case, the color distance will tend to be very small when the value of p_i is close to p_j no matter what the real color distance even these two colors are quit different in visualization. In [16], Mojsilovic et al. modified the color distance measure in Eq. (7) to additive form. The modification can effectively improve the similarity measure. However, the additive-based distance function is linear combination of percentage difference and color distance

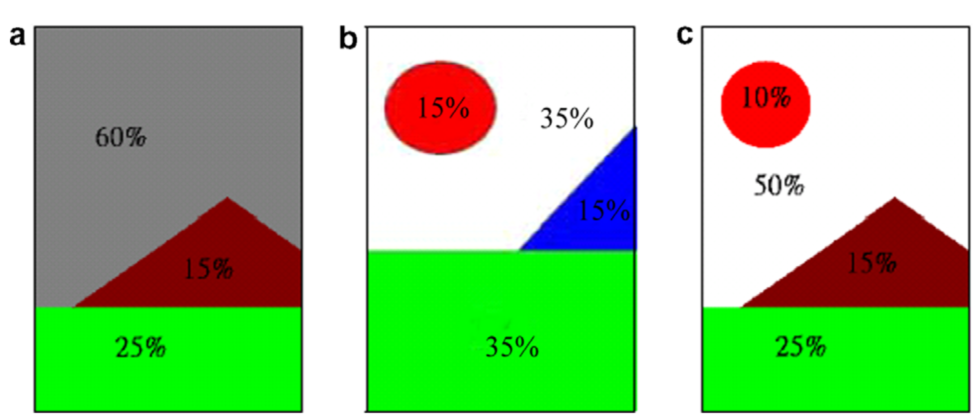


Fig. 3. Artificial image with the dominant colors and their percentage values for example 2: (a) a query image Q, (b) target images F_1, and (c) target image F_2.

in different units, thus normalization of each component is necessary.

In order to solve this problem, we propose a modification on the distance measurement. Considering similarity between a query image and a target image in database, we define the similarity score between two different dominant colors as

$$S_{i,j} = [1 - |p_q(i) - p_t(j)|] \times \min(p_q(i), p_t(j)), \tag{8}$$

where $p_q(i)$ and $p_t(j)$ are the percentages of the ith and jth dominant color in query image and target image, respectively. The $\min(p_q(i),p_t(j))$ is the intersection of $p_q(i)$ and $p_t(j)$, which represents the similarity between two colors in percentage. The term in bracket, $1 - |p_q(i) - p_t(j)|$, is used to measure the difference of two colors in their percentage. If $p_q(i)$ equals to $p_t(j)$, then their percentage is same and the color similarity is determined by $\min(p_q(i),p_t(j))$; otherwise, a large difference between $p_q(i)$ and $p_t(j)$ will decrease the similarity measure. The following two examples are intended to illustrate the advantage of Eq. (8).

1. While $p_q(i) = 0.2$, $p_t(j) = 0.1$, the term of difference measure $= 0.9$, i.e., the difference of two colors in percentages is small; and intersection term $= 0.1$, i.e., the similarity is dominated by $\min(p_q(i),p_t(j))$, and the similarity score in Eq. (8) is quite small.
2. Another extreme example, while $p_q(i) = 0.7$, $p_t(j) = 0.1$, the difference term $= 0.4$, and the value of intersection term is same as above example, so that the difference term will decrease the similarity score. Therefore, the new similarity measure is more reasonable than those of previous methods.

According to Eq. (8), we define a new similarity as follows. Considering two color features $F_1 = \{\{c_i, p_i\}, i = 1,\ldots,N_1\}$ and $F_2 = \{\{b_j, q_j\}, j = 1,\ldots,N_2\}$. Again, the similarity measure SIM is defined as

$$\mathrm{SIM}(F_1, F_2) = \sum_{i=1}^{N_1} \sum_{j=1}^{N_2} a_{i,j} S_{i,j}. \tag{9}$$

In Eq. (9), as mentioned before, $a_{i,j}$ is the coefficient of color similarity, which is determined by the ith and jth dominant color distance. Therefore, the distance between two images F_1 and F_2 is then defined as

$$D^2(F_1, F_2) = 1 - \mathrm{SIM}(F_1, F_2). \tag{10}$$

In order to test the new similarity measure, we calculate the same examples by using Eq. (10). For the first example as shown in Fig. 2, we have

$$D^2(Q, F_1) = 1 - 0 = 1,$$

and

$$\begin{aligned} D^2(Q, F_2) &= 1 - \{1 \times [1 - |0.25 - 0.25|] \times 0.25 \\ &\quad + 1 \times [1 - |0.15 - 0.15|] \times 0.15\} \\ &= 0.6. \end{aligned}$$

Similarly, for the second example as shown in Fig. 3, we have

$$D^2(Q, F_2) = 1 - \{1 \times [1 - |0.25 - 0.35|] \times 0.25\} = 0.775$$

and

$$\begin{aligned} D^2(Q, F_2) &= 1 - \{1 \times [1 - |0.25 - 0.25|] \times 0.25 \\ &\quad + 1 \times [1 - |0.15 - 0.15|] \times 0.15\} \\ &= 0.6. \end{aligned}$$

The results show that the proposed distance measure can effectively address the problems in Eq. (4) and consistent with human perception. As to the computational complexity of the similarity measure, for quadratic distance measure in Eq. (4), the square terms of color percentages of database images can be pre-computed and stored as part of the index, and only 2 subtractions and 1 multiplication need to be computed for on-line retrieval. As compared to quadratic distance measure, the proposed method incurs 2 more comparisons (min and abs) in Eq. (8). However, we think that the slight increases of computation are acceptable.

In the following, we use real images that selected from Corel as examples with actual color and percentage values to enhance the convincingness of our approach. In Fig. 4, the dominant color c_i and their percentage p_i are listed in the first row, the corresponding images are shown in the second row and their quantized images are shown in the last row for visual clarification. We calculate this example using our approach and quadratic-like measure for comparison, and the result can verify the first argument that the number of dominant colors leads to decrease the distance for GLA as we point out aforementioned.

Since the pair-wised distance comparison of all dominant colors in Q and F_1 are exceed T_d, and the quadratic-like dissimilarity measure between these two images is:

$$D^2(Q, F_1) = 0.6732 + 0.249 = 0.9222.$$

On the other hand, we may observe that the quantized images of Q and F_2 are more similar rather than F_1, since the color vectors of R, G, B components in Q, F_2 are very close, and that made Q, F_2 look somewhat "gray level" images. However, the R component is more distinct than other components in F_1, and F_1 is quit different to Q in visualization. However, using the quadratic-like dissimilarity measure between the Q and F_2 is

$$\begin{aligned} D^2(Q, F_2) &= 0.6732 + 0.4489 - 2 \times (1 - 22/50) \\ &\quad \times 0.20576 \times 0.548096 \\ &= 0.9958. \end{aligned}$$

The comparison result of $D^2(Q, F_2) > D^2(Q, F_1)$ is not consistent with human perception. Whereas, using our propose dissimilarity measure, we obtain

$$D^2(Q, F_1) = 1 - 0 = 1$$

and

Query image Q	Target image F1	Target image F2
{(33,31,33),0.794240}	{(66,41,29), 0.108795}	{(60,55,53), 0.378306}
{(184,179,180),0.20576}	{(203,47,71), 0.334035}	{(139,123,115),0.073598}
	{(207,193,59), 0.067861}	{(198,194,188),0.548096}
	{(228,98,161), 0.219045}	
	{(230,162,203),0.270264}	

Fig. 4. Real image examples with the dominant colors and their percentage values. First row: 3-D dominant color vector c_i and the percentage p_i for each dominant color. Middle row: the original images. Bottom row: the corresponding quantized images.

$$D^2(Q,F_2) = 1 - \{(1 - 22/50) \times (1 - |0.20576 - 0.548096|) \times 0.20576\} = 0.9242.$$

Obviously, the proposed method achieves more reasonable results.

The following example will be utilized to explain the second unreason argument of quadratic-like measure for DCD. We may notice that in the quantized image of "rose" in Fig. 5, the darker dominant color $(43, 46, 45)$ occupied 82.21% of color distribution of "rose" image. Whereas, the sum of percentage values of similar dominant colors between Q and F_2 is larger than that of F_1 (92.72% > 82.21%). We may observe that Q and F_2 are more similar in visualization rather than F_1. However, the quadratic-like dissimilarity measure between the two images will lead to $D^2(Q,F_2) > D^2(Q,F_1)$ as follows:

$$D^2(Q,F_1) = 0.532002 + 0.707554 - 2 \times (1 - 5.48/50) \times 0.626495 \times 0.822144 = 0.3223$$

and

$$D^2(Q,F_2) = 0.532002 + 0.498759 - 2 \times [(1 - 17.72/50) \times 0.626495 \times 0.641947 + (1 - 10/50) \times 0.373505 \times 0.28524]. = 0.341.$$

Query image Q	Target image F1	Target image F2
{(47,44,46), 0.626495}	{(43,46,45), 0.822144}	{(40,41,30), 0.641947}
{(194,188,184), 0.373505}	{(189,23,55), 0.177856}	{(138,137, 108), 0.072815}
		{(202,194, 185), 0.28524}

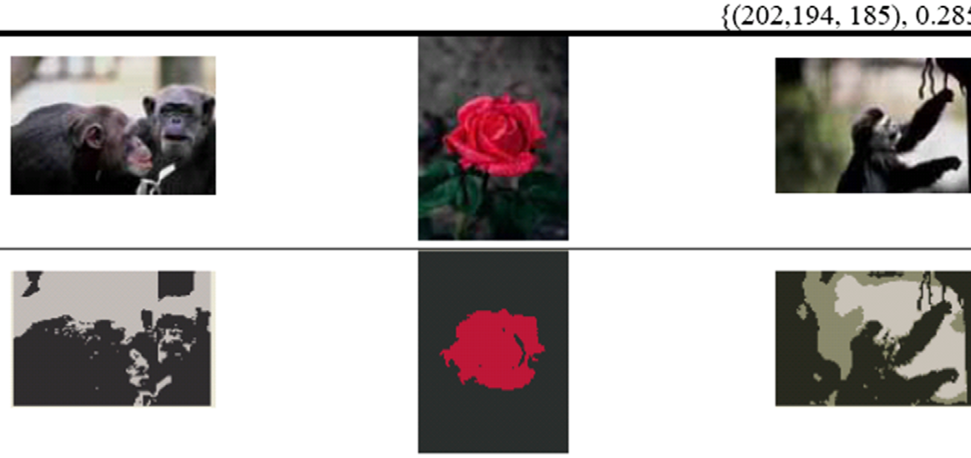


Fig. 5. Real image examples with the dominant colors and their percentage values. First row: 3-D dominant color vector c_i and the percentage p_i for each dominant color. Middle row: the original images. Bottom row: the corresponding quantized images.

Using our proposed similarity measure formulas, we obtain

$$\begin{aligned} D^2(Q,F_1) &= 1 - \mathrm{SIM}(Q,F_1) \\ &= 1 - \{(1 - 5.48/50) \times (1 - |0.626495 \\ &\quad - 0.822144|) \times 0.626495\} \\ &= 0.5513 \end{aligned}$$

and

$$D^2(Q,F_2) = 0.3937.$$

Based on aforementioned analyses, our proposed similarity measure in multiplicative form is more agreeable with perceptually relevant image retrieval for MPEG-7 DCD. Besides, the proposed LBA also extracts representative colors which are more consistent with human perception as shown in Figs. 4 and 5. The experimental results show that the LBA combined the new similarity measure can effectively improve the performance of similarity.

4. Experiments

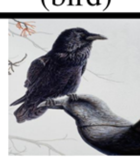
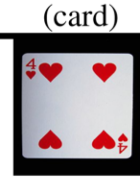
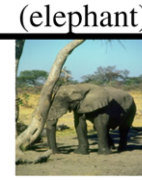
4.1. Color quantization evaluations

We use a database (17 classes about 2100 images) from Corel's photo to test the performance of the proposed method. The database has a variety of images including wild animal, tool, firework, fruit, bird, fish, etc. Table 1 shows the labels for 17 classes and also illustrates an example for each class. The GLA algorithm and the proposed method mentioned in Section 2 are evaluated to compare the effectiveness for dominant colors extraction.

To verify the detailed quantization problem in GLA algorithm as mentioned in Section 2, we illustrate 3 test images from Corel's photo in Fig. 6. For the first example, the dominant colors and quantized results of "card" image by proposed method (LBA) and GLA algorithm are shown in the first row of Fig. 6, respectively. We can easily find that the quantized image using GLA seems very sensitive to brightness so that it generates undesired partition due to the shadow in the card. On the other hand, the quantized image by our proposed method preserved the majority of colors in the original image. Subjectively, the quantized performance of the proposed method is better than that of the GLA algorithm. Furthermore, we also developed the detailed numerical analysis using two sets of dominant colors $\boldsymbol{X}_1$ and $\boldsymbol{X}_2$ which were extracted from "card" image by our method and GLA algorithm, respectively.

1. In visualization, there are three main colors in "card" image, i.e., "black" for border, the color of digit and heart shape is "red" and the rest region is "white". We may observe that the quantized result by LBA is more consistent with original image as comparing to GLA. As to compare the number of dominant colors, LBA is more compact than GLA.

Table 1
The illustration of the test database

Class 1 (gorilla)	Class 2 (bird)	Class 3 (potted plant)	Class 4 (card)	Class 5 (cloud)	Class 6 (sunset)
					
Class 7 (pumpkin)	Class 8 (cake)	Class 9 (dinosaur)	Class 10 (whale/dolphin)	Class 11 (elephant)	Class 12 (firework)
					
Class 13 (body-building)	Class 14 (flower)	Class 15 (wall-painting)	Class 16 (duck)	Class 17 (tool)	
					

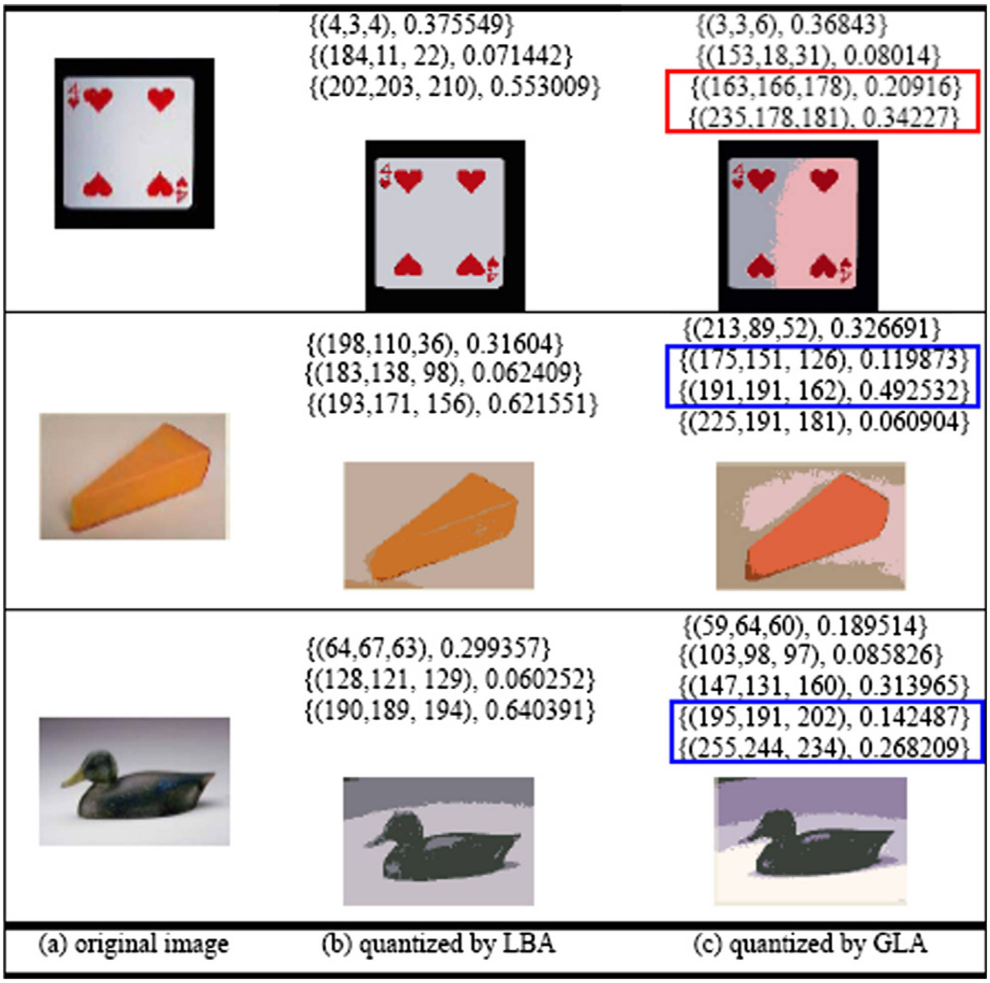


Fig. 6. Comparisons of quantization performance for our proposed LBA and the GLA algorithm. (a) Original images from Corel's photo, (b) dominant colors extraction and quantized image by LBA, (c) dominant colors extraction and quantized by GLA.

2. Objectively, we use actual dominant color vectors and percentage values for comparison; the two sets of dominant colors $\boldsymbol{X}_1$ and $\boldsymbol{X}_2$ extracted by LBA and GLA are

$$\boldsymbol{X}_1 = \{\{(4,3,4), 0.375549\}, \{(184,11,22), 0.071442\}, \{(202,203,210), 0.553009\}\}$$

and

$$\boldsymbol{X}_2 = \{\{(3,3,6), 0.36843\}, \{(153,18,31), 0.08014\}, \{(163,166,178), 0.20916\}, \{(235,178,181), 0.34227\}\}.$$

We may observe that our quantized scheme is more consistent with human perception also. Whereas, GLA will partition the visual "white" region into two dominant colors (marked by red rectangle box), since the GLA algorithm is based on minimum quantization distortion rule.

3. In general, the variance of a finite population can measure of how spread out a distribution is. We calculate the variance of these two sets of dominant colors $\boldsymbol{X}_1$ and $\boldsymbol{X}_2$, we obtain $\sigma^2(\boldsymbol{X}_1) > \sigma^2(\boldsymbol{X}_2)$. The analysis of variance applies to this example reveals that our quantized approach is more suitable to conform to the characteristics of dominant colors than GLA.

For the "cake" and "duck" images in Fig. 6 (the second and third rows), the intrinsic minimum distortion rule in GLA will lead to partition the similar color into different representative colors (marked by blue rectangle boxes in Fig. 6). However, it can be seen that the extracted dominant color vectors by our proposed method is more distinct and the quantized image can preserve the majority of colors in the original image as comparing with GLA.

As to the analysis of computational complexity of LBA and GLA, since the LBA is based on simple quantization and merging rules; whereas, the DCD extraction by GLA algorithm performs greedy mutual distance calculations, minimizes distortion and iterates until the convergence condition is satisfied. On the contrary, the LBA is a simple rule as mentioned in Section 2. Although we do not provide the detailed numerical analysis, the qualitative analysis on the computational complexity of our proposed method is significantly less than that of GLA algorithm. Based on aforementioned observations, our proposed method reveals the effectiveness for color quantization and quantized performance of the LBA is better than that of the GLA.

4.2. Visual comparisons of retrieved images

To illustrate the retrieval performance of the proposed method, we simulate a large number of query tests, and the representative results are shown in Fig. 7. In the retrieval interface, the query image is on the left and the top 20 matching images are arranged from left to right and top to down in the order of decreasing similarity score.

In Fig. 7(a) and (b), the retrieving results are using MPEG-7 distance measure and proposed method, respectively. In this example, the query image is an elephant in the wild. The analyses of retrieval performance are as follows:

1. The MPEG-7 distance measure returns 18 visually matched images; whereas our proposed returns 19.
2. In Fig. 7(a), MPEG-7 distance measure retrieves two very dissimilar images (marked by red rectangle boxes), which have ranks of 14 and 18, respectively. From the dominant color vectors and quantized images in Fig. 8,

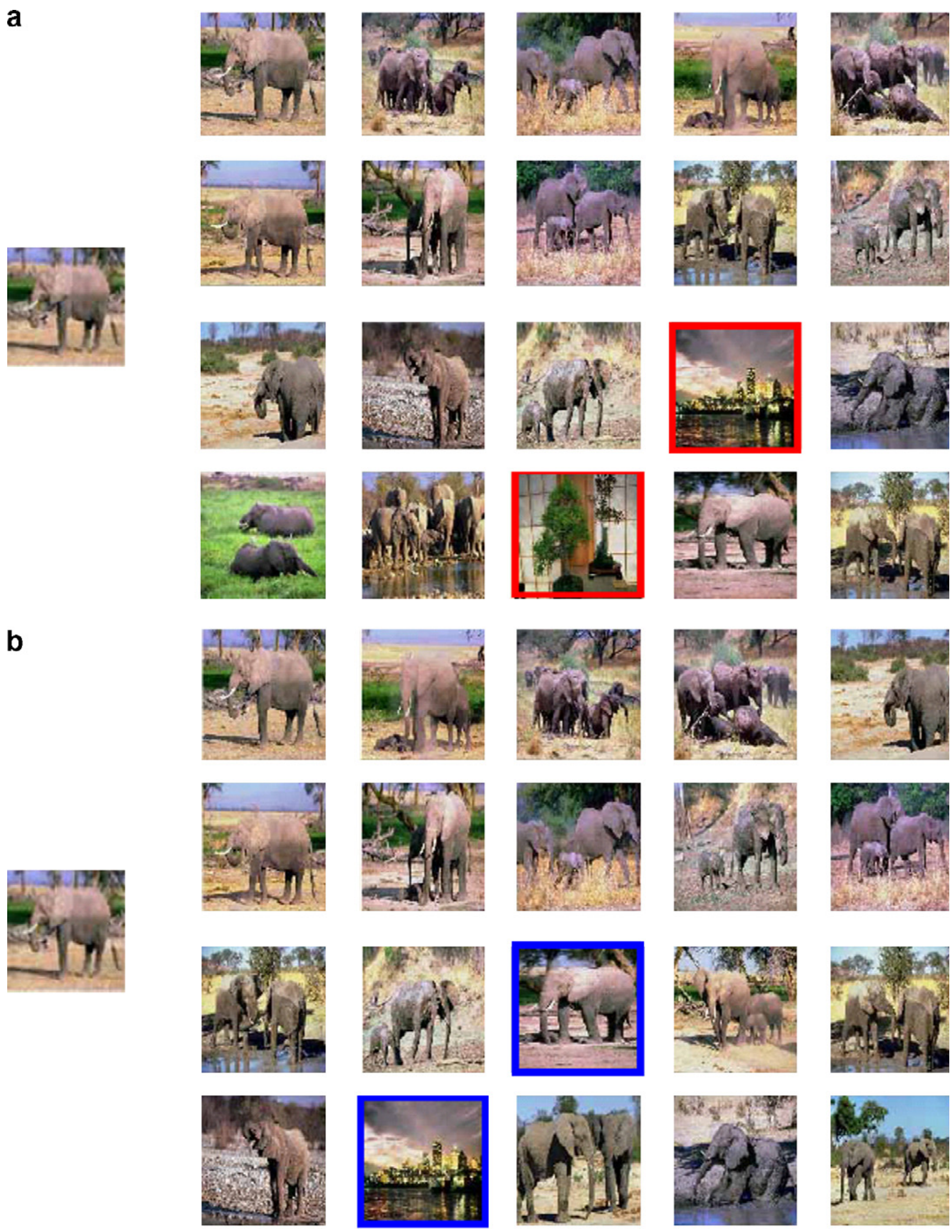


Fig. 7. Comparisons of retrieval results using MPEG-7 dissimilarity measure and our proposed method. (a) Using quadratic-like measure, (b) using proposed dissimilarity measure.

Query image Q	Target image F1	Target image F2
{(80,78,62),0.325531}	{(71,65,56), 0.586151}	{(60,60,52),0.389832}
{(135,118,112),0.094218}	{(135,117,109),0.129557}	{(146,122,114),0.140238}
{(174,145,115),0.120728}	{(173,153,100), 0.07028}	{(196,165,165),0.46993}
{(196,168,157),0.459523}	{(202,185,166), 0.21401}	

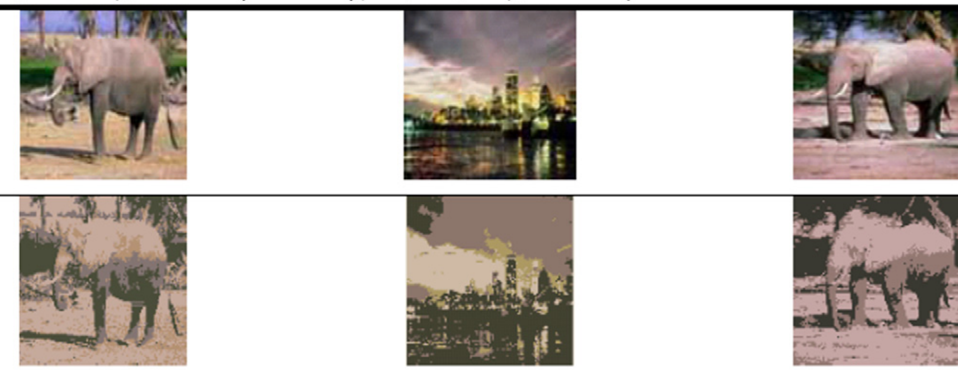


Fig. 8. First row: 3-D dominant color vector c_i and the percentage p_i for each dominant color. Middle row: the original images. Bottom row: the corresponding quantized images.

the colors of "elephant" and "ground" in query image are similar to the sky color in "sunset" image, which cause the improper ranks. However, using our proposed similarity measure, the rank of these two images is 17 and 31, respectively.

3. Furthermore, for better understanding of the retrieval performance of new method, the dominant color vectors of query image and two retrieved images are shown in Fig. 8. One of the two images is dissimilar image "sunset" with rank 17 and the other one is very similar image "elephant" with rank 13, and they are marked by blue rectangle boxes in Fig. 7(b), respectively. In Fig. 7(a), we found that the ranks of these two images are 14 and 19 by using the MPEG-7 distance measure. In this case, we observe from Fig. 8 that the first dominant color with a higher percentage (marked by red box) in "sunset" image is similar to the first dominant color in query image (marked by blue box), and the sum of percentage values of similar colors between Q and F_1 is larger than that of F_2 also. In this example, the quadratic-like dissimilarity measure of these two images are $D^2(Q, F_1) = 0.3477$ and $D^2(Q, F_2) = 0.3549$. Due to $D^2(Q, F_1) < D^2(Q, F_2)$, it makes the unreasonable result.

However, using the proposed similarity measure in Eq. (10), we obtain $D^2(Q, F_1) = 0.6154$ and $D^2(Q, F_2) = 0.5544$. We investigate the result and find out some noticeable observations as follows:

1. Although, the sum of percentage values of similar colors between Q and F_2 is smaller than that of F_1. However, both the color and percentage of last dominant color vector $\{(196, 165, 165), 0.46993\}$ in F_2 is very similar to the last dominant color $\{(196, 168, 157), 0.459523\}$ in Q.
2. We calculate the similarity score between these two dominant colors by Eq. (9), i.e.,

$$\begin{aligned} \mathrm{SIM} &= (1 - 8.54/50) \times (1 - |0.459523 \\ &\quad - 0.46993|) \times 0.459523 \\ &= 0.37707, \end{aligned}$$

and the similarity score will lead the distance measure in Eq. (10) decrease dramatically.

Based on aforementioned observation, it implies that our approach considers properly not only the similarity of dominant colors but also the difference of color percentages between images. As shown in Fig. 7(b), the retrieval results reveal the perceptually relevant image of our approach. It can be seen that the performance of the proposed method is better than that of MPEG-7 distance measure.

4.3. The comparisons of average retrieval rate and rank

In order to make a comparison on the retrieval performance, both average retrieval rate (ARR) [13] and average normalized modified retrieval rank (ANMRR) are applied. An ideal performance will consist of ARR values equal to 1 for all values of recall. A high ARR value represents a good performance for retrieval rate, and a low ANMRR value indicates a good performance for retrieval rank.

To evaluate the retrieval performance, all images of the 17 classes are used as queries. The quantitative results for individual class and average performance are tabulated in Tables 2–5 for comparing the performance with different combinations, also compare with palette histogram similarity measure proposed by Po and Wang

Table 2
Comparisons of ANMRR performance for the MPEG-7 dominant color (GLA) with different similarity measure

Method: Class	GLA/MPEG-7 similarity measure	GLA/palette histogram measure	GLA/our proposed measure
1	0.685	0.660	0.672
2	0.787	0.742	0.748
3	0.731	0.713	0.697
4	0.677	0.591	0.533
5	0.724	0.726	0.710
6	0.722	0.745	0.719
7	0.839	0.870	0.858
8	0.629	0.742	0.710
9	0.725	0.683	0.674
10	0.718	0.608	0.612
11	0.715	0.746	0.720
12	0.681	0.531	0.535
13	0.763	0.746	0.726
14	0.777	0.807	0.788
15	0.579	0.601	0.583
16	0.669	0.675	0.638
17	0.847	0.799	0.797
Average	0.722	0.705	0.689

Table 3
Comparisons of ARR performance for the MPEG-7 dominant color (GLA) with different similarity measure

Method: Class	GLA/MPEG-7 similarity measure	GLA/palette histogram measure	GLA/our proposed measure
1	0.349	0.422	0.386
2	0.287	0.353	0.312
3	0.308	0.309	0.329
4	0.437	0.613	0.620
5	0.327	0.324	0.333
6	0.296	0.313	0.319
7	0.160	0.119	0.142
8	0.358	0.286	0.314
9	0.371	0.476	0.441
10	0.378	0.484	0.484
11	0.333	0.314	0.342
12	0.483	0.896	0.869
13	0.331	0.295	0.331
14	0.304	0.315	0.339
15	0.510	0.483	0.507
16	0.389	0.381	0.412
17	0.199	0.278	0.274
Average	0.342	0.392	0.397

Table 4
Comparisons of ANMRR performance for proposed fast color quantization approach (LBA) with different similarity measure

Method: Class	LBA/MPEG-7 similarity measure	LBA/palette histogram measure	LBA/our proposed measure
1	0.554	0.490	0.517
2	0.551	0.514	0.553
3	0.602	0.560	0.562
4	0.211	0.211	0.186
5	0.672	0.686	0.650
6	0.722	0.689	0.690
7	0.673	0.695	0.641
8	0.575	0.644	0.616
9	0.215	0.270	0.186
10	0.579	0.500	0.491
11	0.455	0.544	0.491
12	0.155	0.052	0.056
13	0.477	0.585	0.481
14	0.753	0.784	0.758
15	0.380	0.417	0.393
16	0.427	0.429	0.386
17	0.685	0.566	0.586
Average	0.511	0.508	0.485

Table 5
Comparisons of ARR performance for proposed fast color quantization approach (LBA) with different similarity measure

Method: Class	LBA/MPEG-7 similarity measure	LBA/palette histogram measure	LBA/our proposed measure
1	0.528	0.633	0.560
2	0.453	0.493	0.487
3	0.494	0.532	0.534
4	0.937	0.965	0.965
5	0.422	0.395	0.419
6	0.298	0.364	0.366
7	0.327	0.278	0.348
8	0.416	0.366	0.407
9	0.827	0.640	0.816
10	0.670	0.635	0.673
11	0.622	0.548	0.597
12	0.880	0.943	0.966
13	0.612	0.429	0.551
14	0.363	0.360	0.382
15	0.730	0.674	0.714
16	0.659	0.647	0.704
17	0.393	0.485	0.554
Average	0.566	0.552	0.591

[8]. First, we adopt the conventional quantization method (MPEG-7 dominant color) to evaluate the performance of different similarity measure (MPEG-7 quadratic-like measure, palette histogram measure and our modified distance measure) in Tables 2 and 3. It can be seen from Tables 2 and 3 that our proposed modified distance measure provides the best retrieval rank and rate. Therefore, we can claim that the modified distance function is suitable for DCD matching. Furthermore, the evaluation of our quantization approach (LBA) with different similarity measure is listed in Tables 4 and 5; it is shown that our integrated method (LBA + our modified distance function) achieves ARR improvement rates by 4.2% and 6.6%, and raises 5.4% and 4.8% in term of ANMRR over conventional MPEG-7 DCD and palette histogram similarity measure [8], respectively.

Table 6
The comparisons of ARR/ANMRR performance for proposed similarity measure with Ma [14] and Mojsilovic [16]

Method:	LBA/our proposed measure		LBA/$\|p_i - p_j\| \times D\ (c_i - c_j)$		LBA/$\|p_i - p_j\| + D\ (c_i - c_j)$	
Class	ARR	ANMRR	ARR	ANMRR	ARR	ANMRR
1	0.560	0.517	0.389	0.584	0.535	0.528
2	0.487	0.553	0.366	0.584	0.478	0.526
3	0.534	0.562	0.389	0.666	0.491	0.629
4	0.965	0.186	0.873	0.429	0.964	0.228
5	0.419	0.650	0.348	0.659	0.419	0.629
6	0.366	0.690	0.362	0.644	0.473	0.568
7	0.348	0.641	0.366	0.613	0.448	0.581
8	0.407	0.616	0.354	0.622	0.378	0.595
9	0.816	0.186	0.454	0.399	0.715	0.284
10	0.673	0.491	0.505	0.557	0.562	0.518
11	0.597	0.491	0.449	0.580	0.517	0.553
12	0.966	0.056	0.446	0.396	0.920	0.228
13	0.551	0.481	0.400	0.600	0.544	0.563
14	0.382	0.758	0.428	0.675	0.507	0.657
15	0.714	0.393	0.608	0.477	0.643	0.473
16	0.704	0.386	0.474	0.538	0.658	0.460
17	0.554	0.586	0.405	0.564	0.494	0.543
Average	0.591	0.485	0.448	0.564	0.573	0.504

In the following, we also compare the performance of our method with two previously proposed similarity measure methods [14,16] in Table 6. We may notice that the unsatisfactory retrieval result by Ma [14] is expected; compared to Mojsilovic [16], our proposed approach achieves 3% and 4% improvement rates in terms of ARR and ANMRR.

Generally, an image database collects variety of images including wild animal, tool, firework, fruit, bird, fish, etc. Based on our observation, the collected images possibly contain various features, such as texture, shape, and color. It is difficult to achieve precious and satisfactory retrieving results perfectly by using only single feature descriptor. In order to satisfy human perception completely in retrieving process, the combination of multiple feature descriptors or using more advanced retrieving technique such as relevance feedback should be considered. However, in this paper, we aim to develop a dominant color descriptor with effective and efficient extraction scheme and similarity measure. Simulation results show that our fast quantization scheme is better than GLA in visualization and the new similarity measure in a multiplicative form, which is more consistent with human perception than the conventional quadratic-like measure. The integrated approach achieves better performance for image retrieval than that of conventional MPEG-7 DCD, and also performs better than [8].

5. Conclusion

In this paper, we have presented a color quantization method for dominant color extraction, called the linear block algorithm (LBA). It has been shown that LBA is efficient in color quantization and computation. In addition, we have introduced a modification in dissimilarity measure, which improves the performance for image retrieval. A combination of LBA and modified dissimilarity technique has been implemented. The new DCD scheme is very computational efficiency. In addition, the proposed similarity measure is consistent with human perception and the experimental results indicated that the proposed technique improves retrieval performance in terms of both ARR and ANMRR.

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