

## Efficient, Compact, and Dominant Color Correlogram Descriptors for Content-based Image Retrieval

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**Abstract**— Color is one of the most important and widely used cues in content analysis and retrieval. However, most promising color descriptors consume massive amounts of computation and storage, which is a serious drawback. One of these promising color techniques in image retrieval is the color correlogram, but the technique also suffers from the aforementioned drawbacks. In this paper, we present two compact representations of the color correlogram. The first representation is the compact-generalized correlogram, which compresses colors and generalizes the distances of the original correlogram descriptor. The second representation is the dominant color-based correlogram, which is also a compact and conceptual correlogram descriptor. This representation computes the spatial correlations of the dominant colors of a few images instead of a large number of quantized colors used by the original descriptor. The two representations are integrated. The experimental results prove the high effectiveness and feasibility of the proposed descriptors through two large image databases (i.e., Corel-10K and Cartoon-11K) using ARR, ANMRR, P(10), and MAP metrics.

**Keywords**—Color Correlogram; Large database; Dominant Color; Compact descriptor; Content-based Image Retrieval

### I. INTRODUCTION

Color descriptors play an important role in reducing the gap between low-level features, such as color, texture, and shape, and high-level semantic concepts, such as emotions, events, or scenes [1][2]. Color is considered a powerful cue for content-based image retrieval (CBIR) [3][4] and is also an effective feature in image analysis because color is robust with noise, image orientation, and resolution [2][4–6]. Therefore, various color descriptors have been proposed in previous studies [7–9]. The color histogram [7] and its enhancements [10–12] are good attempts at creating color descriptors because of their ability to solve translation and rotation invariant problems. However, the color histogram and its enhancements lack the spatial correlation of colors that allows different images to be considered similar.

One of the most promising approaches in solving the problem is color correlogram [13][14], which preserves the spatial correlations of color information for accurate image retrieval. The color correlogram approach demonstrates high effectiveness compared with the color histogram and an earlier spatial-color approach called the color coherence vector (CCV) [9]. The color correlogram is a table indexed by color pairs  $(C_i, C_j)$ , where the  $k^{\text{th}}$  entry specifies the probability of finding a color  $C_i$  at a distance  $k$  from a color

$C_j$  in the image;  $i, j$  are the indexes of colors within a range of  $m$  quantized colors; and  $k$  is a distance within the range of a maximum distance  $d$ .

The problem of the correlogram lies in the expensive cost of memory space and computation time, with the correlogram requiring  $O(m^2d)$  complexity. This cost is an infeasibility problem for use in a huge database, especially regarding memory space. Several gigabytes are required for a large database, which may not be available in the main memory of a computer. Therefore, the *Autocorrelogram* [13] is proposed to reduce the time and space complexity into  $O(md)$  by finding the spatial correlation of each color with only itself. The accuracy of the *Autocorrelogram* is certainly lower than the original correlogram because the correlations of a particular color with other colors are ignored, and the only correlation with the same color is kept.

In this paper, a compact and generalized representation of the color correlogram is proposed, which reduces the complexity of the correlogram from  $O(m^2d)$  to  $O(m^2/2 + m/2)$ . The proposed representation is slightly more complex than the *Autocorrelogram* (or less complex than the *Autocorrelogram* in some cases when  $d$  is large). The proposed method outperforms the *Autocorrelogram* and achieves the same (or slightly lower) accuracy than the original correlogram. The satisfactory performance is caused by the preservation of the spatial correlations among all the colors in the image, which reduces the memory space of the colors ( $m^2$ ) to approximately half ( $m^2/2 + m/2$ ). The proposed representation also generalizes all  $d$  distances into one distance value by taking the average of all distances. In this case, keeping many distances that refer to separate spatial correlations becomes expensive. Instead, averaging the distance significantly reduces the complexity of the descriptor with very little degradation in accuracy.

Color descriptors, including the color correlogram, are weak in image recognition or discrimination because the naive rules that the color descriptors are based on do not simulate the human visual system [3][4]. Therefore, more improvements can be done in this field. Much research has been conducted on human color perception (e.g., [15][16]), which show that humans use only a few of the prominent or dominant colors of the image to judge similarity. Two rules on the model human visual and color perception exist. The first rule states that two images are considered similar if the images have the same dominant colors (DCs). The second rule indicates that the two images are perceived to be similar if the images have the same distribution of DCs irrespective

of content [4]. Humans consider the DCs and the spatial distributions of images to judge color similarity. Therefore, dominant color descriptors have been introduced in many studies (e.g., [17–20]) instead of descriptors that use a large number of colors, such as the color histogram and color moments [7][10][12].

The color correlogram has perceptual and infeasibility problems in large databases. Thus, a perceptual correlogram was introduced [4], which applies *ColGrm* concepts on a few DCs instead of a large number of colors. However, the perceptual correlogram has some deficiencies in simulating the original correlogram through the imperfect similarity measure, which will be explained in Section IV. In the present paper, an adaptation of the perceptual correlogram [4] is proposed. The adapted descriptor is called a DC-based color correlogram (DCBC), which adapts the dissimilarity measure of the perceptual correlogram by correctly simulating the original correlogram on a few dominant colors.

The rest of this paper is organized as follows: Section II presents the related works on the color-based CBIR. Section III introduces the compact-generalized correlogram (CGC), and Section IV presents the adapted perceptual DC-based correlogram. The experimental results of the proposed and adapted descriptors and their integration are compared with some candidate descriptors in Section V. Section VI concludes the paper.

## II. RELATED WORK

Many studies have been conducted on content-based image retrieval (CBIR), such as Visual-SEEK [21], QBIC [22], Photobook [23], and Image-Rover [24]. In these studies, several visual (low-level) features, such as color, texture, and shape, were used. Color is one of the most commonly used features in CBIR [3][4]. Therefore, this study focuses solely on color to retrieve images in the CBIR domain.

Previous studies vary in their usage of color descriptors [3]. Some use global color descriptors (GCDs), and others used spatial color descriptors (SCDs). The former is used to measure the similarity between two images by taking the colors and their percentages in the images into account, such as the color histogram [7][10] and the dominant colors [17–19][28]. The latter measures the similarity between the two images by considering the existing colors and their distributions or arrangements in the image, such as in the CCV [9] and color correlogram [13][14].

The color histogram in GCDs proposed in [7] has been extensively used as a GCD to solve translation and rotation invariant problems. This color histogram is characterized by easy implementation and accuracy particularly in small databases. Many enhancements in histogram-based approaches have been achieved, as reported in [10][11][25]. The original representation of the RGB color is 24-bits 16-million colors that are assigned to each pixel in the image, leading to an infeasibility problem for both time and memory space. Therefore, static quantization [39] is used to reduce color space to make storage and time more reasonable. However, histogram-based approaches have several

drawbacks. The first one is the dependence on a static quantization method, which suffers from low discrimination power. The lack of discrimination is caused by a large number of similar colors set to different bins, making the similarity measure (i.e., L1, L2 or histogram intersection) between the two histograms inefficient. The second drawback is the mismatch of the methods with human color perception [19][26][28]. Humans cannot perceive more than eight colors [27] or can only perceive a few prominent colors in an image [4][15][16]. Therefore, extracting DCs from the image becomes the best solution because DCs require less time and storage consumption.

Although DCs are not that effective in color-based image retrieval, it is still considered a GCD. The basic problem of these descriptors is the lack of spatial correlations of colors within the image. This absence leads to considering different images in terms of color distribution as similar because of the same color percentages. The complement part (spatial relationship of colors) of the similarity of images is “where the colors are located” [3][4]. GCDs work without the complement part; thus, the results are not satisfactorily presented in the CBIR field. Many methods have been proposed to include the complement part, such as the CCV [9]. A pixel is considered coherent if its color is similar to the color of the region to which it belongs; otherwise, the pixel is considered incoherent. Many approaches have also been proposed to prove the high effectiveness of the spatial relationship among image colors such as [29], which used the concept of color boundaries, and [5][8], which used the color adjacency concept. These approaches lead to a simple conclusion that the relative distance (inter-distance) of the colors of an image can capture the true or real composition of the colors in the image.

These SCDs have two important properties: translation and rotation invariant. One of the most active approaches among all the SCDs is the color correlogram (*ColGrm*) [13][14]. The *ColGrm* is a table indexed by color pairs ( $C_i, C_j$ ), where the  $k^{th}$  entry specifies the probability of finding a color  $C_i$  at a distance  $k$  from a color  $C_j$  in the image;  $i, j$  are indexes of the colors within the range of  $m$  quantized colors; and  $k$  is the distance within the maximum distance  $d$ .

The *ColGrm* complexity is  $O(m^2d)$ , which consumes high CPU time and memory space, especially in a large database. For example, the image of width ( $W=500$ ) and height ( $H=400$ ) is assumed. In such dimensions, a suitable value for  $d$  would be 40–200, corresponding to the following formula:  $d \approx 10\%$  to  $50\%$  of the smaller dimensions in the image [2][3]. Any value of  $d$  less than this range will not be suitable in capturing the true spatial color distributions of the image because only colors within a small range will be described. The complexity of correlogram algorithm remains too high and requires several processing hours per image on a computer even with a lower bound selection of the range of distance  $d$  ( $d=40$ ). Moreover, an infeasible memory space for the feature vector will be required even for a small image database. Several possible solutions can be applied to solve this infeasibility problem. The first solution is the reduction of the range of distance  $d$  (e.g., let  $d \approx 10$ ), which will reduce the complexity by only fourfold (an insignificant reduction)

and will be unable to precisely identify the true spatial color distribution. Another solution is the reduction of the color space using the quantization algorithm. The typical quantization for RGB color space is 8 partitions for each band ( $8 \times 8 \times 8$ ), which will equal to 512 colors and will speed up the ColGrm by about 30-fold. However, immense memory space (about 80 megabytes (MB) per image) will still be required, making the ColGrm applicable for only small databases. Therefore, a simplified version of the ColGrm called *AutoCorrelogram* is introduced [13]. The *Autocorrelogram* only characterizes the spatial color distribution of the same colors, i.e., each color with itself without identifying correlations with other colors. The latter case may cause the degradation of the color descriptor, which actually occurred in many studies [1–4][13][14] that reported the ColGrm to be better in retrieval accuracy than the *Autocorrelogram*.

Ma and Zhang [30] and recently [31][32] show (using extensive experiments) that the ColGrm and Autocorrelogram can achieve better performance than those of other global and spatial color descriptors, such as the color histogram, color moments, and CCV, despite the limitations of correlograms. Some extensions were made to both, such as the Markov Stationary Features [33], which is an extension of the Autocorrelogram, Wavelet Correlogram [34], and Gabor wavelet correlogram [35]. All these approaches perform only slightly better than the original ColGrm descriptor, which has more time complexity [4]. A recent method reduces the time complexity of ColGrm by the approximation of a descriptor [36], depending on the randomization of selecting the neighbors of the pixels. The method certainly decreases the accuracy compared with the original ColGrm but decreases time complexity to half. The drawbacks of this method are that the complexity of the memory space remains  $O(m^2d)$  and that the accuracy of such an algorithm is not fixed because of the dependence on the randomization of selecting the candidate pixels to build the ColGrm feature vector. Therefore, the proposed method depends on the original ColGrm in adaptation and comparison. A compact representation of the ColGrm is proposed in this paper to solve the problem of infeasibility. The details of the proposed method are presented in Section III.

DC-based methods can be used to solve the perceptual and infeasibility problems of the color histogram. However, the DC-based methods remain as GCDs and lack spatial color correlations. Therefore, the DC concept can be integrated with the ColGrm to obtain better performance than when each is applied separately. A satisfactory attempt was recently conducted to integrate the two in [4], which used a penalty trio model to find the dissimilarity between the two images by joining the global (from DCs) and the spatial (from ColGrm) information. Kiranyaz et al. [4] changed the dissimilarity equation of ColGrm, which is claimed to be inefficient, but such change would lead to serious performance degradation. This problem will be discussed in more detail in Section IV. A duo-model instead of a trio-model is proposed to solve the problem of the later model.

### III. THE PROPOSED CGC DESCRIPTOR

The color correlogram offers the best performance among the GCDs and SCDs, as mentioned in Section II. However, the massive consumption of time and memory space remains its major drawback. Some reduction can be achieved for its time and feature vector space through a critical analysis of the process of the correlogram.

ColGrm  $\gamma_{ci,cj}^{(k)}$  is a table of probabilities for finding the spatial correlation of a certain color with the other colors within an image from a specific distance. The table is indexed by the triple  $(Ci, Cj, k)$ , where  $Ci$  and  $Cj$  represent the colors their neighboring probabilities need to know in a distance  $k$ . The indexes' values  $i, j$  are within the  $m$  quantized colors, and the  $k$  value is within the maximum distance  $d$ . The ColGrm maintains spatial correlation among the colors in the image. The ColGrm table is depicted in Figure 1.

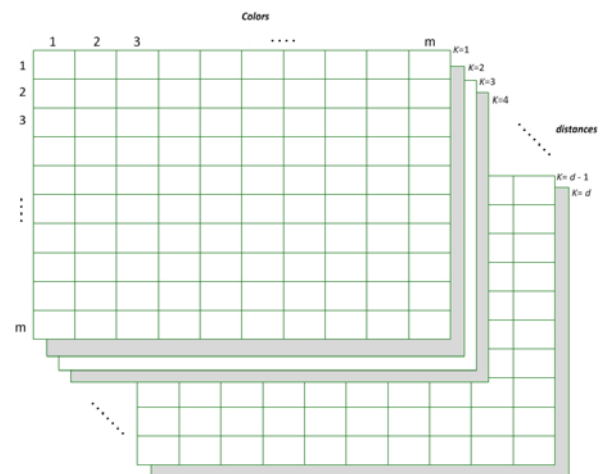


Figure 1. Original color correlogram feature vector representation with a complexity of  $O(m^2d)$ .

Figure 1 shows that the massive storage space of this representation lies in the colors and distances. Therefore, our proposed method is focused on the reduction of these two factors without a significant degradation of the performance of the original ColGrm.

#### A. Color Reduction

In the first factor (colors), the square matrix of colors in Figure 1 contains the probabilities of finding color  $i$  at the distance  $k$  from color  $j$ . A repetition of information is noticeable through a proper logical analysis of this color representation. The probability of finding color  $i$  with a specific distance from color  $j$  is located in the two positions in the matrix: locations  $(i, j)$  and  $(j, i)$ . Intuitively, the existence of a white color beside a black one, for example, has the same meaning as a black color being beside a white one. Black is on the right of white; thus, we can find white on the left of black. The co-occurrence matrix of the colors in the original representation increases in the two locations co-occurrence (black, white) and co-occurrence (white, black), as shown in Figure 2.

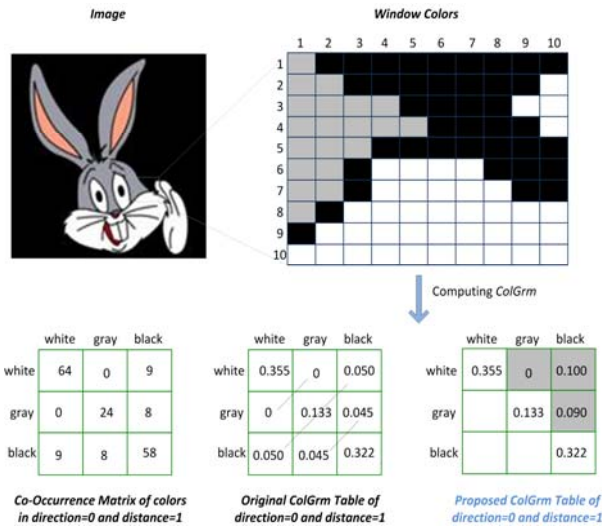


Figure 2. An example of computing the ColGrm table in the image window in a simple setting (direction = 0 and distance = 1), which shows the similarity of the lower rectangular matrix with the upper one.

Figure 2 is an example of the image window that has three colors, namely, white (w), gray (g), and black (b). A simple setting (direction = 0 and distance = 1) is considered as a simple explanation to the reader. The direction equal to zero and the distance equal to one indicate that only the horizontal (left and right) neighbors of the pixels are considered during the extraction of the ColGrm table. The elements of the co-occurrence matrix are shown in Figure 2. For example, the co-occurrence (white, black) = 9 means that 9 horizontal black neighbors to the white color exist. The ColGrm table holds the probability instead of the number of the occurrence of colors; thus, the co-occurrence matrix is simply divided by the number of all neighbors in the 10 × 10 window, which is 180. The ColGrm table shows that ColGrm (w, g) = ColGrm (g, w) and all the other elements in the lower triangular matrix are similar to the elements of the upper matrix. Therefore, repeating these elements is useless because one element is sufficient for each of the two colors instead of two elements. Keeping the upper triangular matrix with the main diagonal is enough to maintain the whole matrix. The upper triangular matrix in the new proposed representation is duplicated to substitute the absence of the lower matrix. The ColGrm complexity can be reduced to approximately half, i.e.,  $O(m^2/2+m/2)$  instead of  $O(m^2)$ , as shown in the shaded cells of Figure 3. Therefore, only the upper triangular matrix and the main diagonal must be computed and saved.

The dissimilarity measure equation remains the same as the original correlogram, as depicted in (1) [13][14].

$$ColGrmDisSimilarity(Q,I) = \sum_i \sum_j \sum_k^d \frac{|\gamma_{ci,cj}^{(k)}(Q) - \gamma_{ci,cj}^{(k)}(I)|}{1 + \gamma_{ci,cj}^{(k)}(Q) + \gamma_{ci,cj}^{(k)}(I)} \quad (1)$$

### B. Distance Reduction

Distance is the second specified factor in reducing the complexity of the ColGrm feature vector. The number of distances required for the ColGrm to capture the true spatial correlations of the colors ranges from 10% to 50% of the smaller dimension in the image. This process consumes CPU time and memory space, as depicted in Figure 1.

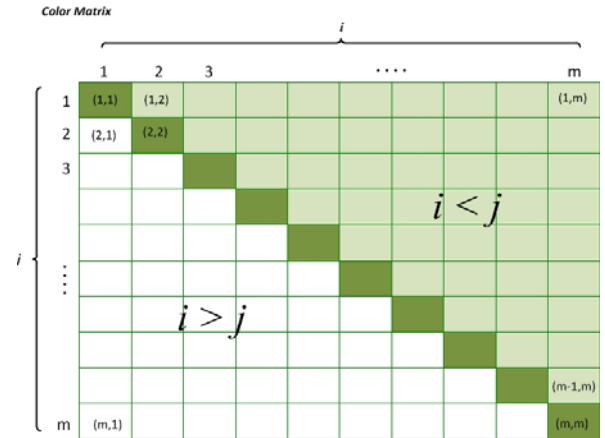


Figure 3. New ColGrm matrix representations. The shaded cells represent the actual required storage space for the colors (approximately half the size of the colors in the ColGrm).

The reduction of time and space is required to apply the ColGrm in a large database. The proposed solution to reduce these distances is generalization. The proposed generalization scheme that can be applied for distances is to average all distances. Distances are very important in measuring how many pixels exist between a certain color and other colors. For example, the image with three colors in Figure 2, where  $d = 1$  and ColGrm (white, gray, d) = 0.15, indicates that the probability of finding a white color far from a gray color by one pixel is 0.15. When  $d = 2$  and ColGrm (white, gray, d) = 0.149, the probability of finding a white color from a gray color by two pixels is 0.149. This pixel-based structure is unfortunately one of the main drawbacks of the ColGrm [3][4] because the color vicinity is characterized at a pixel level, which is unfeasible (in terms of time and space) in high resolution images and has no meaning with regard to the human visual system. The individual pixels cannot be perceived by the human eye. The average of all distances can be computed to eliminate this effect from the ColGrm and generalize the distance. The layers of the distance shown in Figure 1 can be abbreviated to one layer that contains the probabilities of generally finding the colors in the image I. In Figure 1, the size of the image is 10 × 10; thus, a distance = 5 is selected as 50% of the smaller dimension in the image. When distance = 5 and the generalization of ColGrm is applied, one layer is produced. For example, ColGrm (white, gray) = 0.145 means that the probability of finding the white color far from the gray color by 3 pixels (average of 5 distances is 3) is generally 0.145. This process ensures the generality of the descriptor and eliminates pixel-level dependency (especially in high-resolution images). The spatial correlations of the

colors in general for all the images in the database are also described. A general vision of the image contents (colors) is drawn instead of depending on the individual distances of the colors that lack feasibility and human perception. The complexity of the distance becomes 1 (instead of  $d$  in original *ColGrm*). The total complexity of the proposed *ColGrm* after color and distance reduction becomes  $O(m^2/2+m/2)$  instead of  $O(m^2d)$ , as shown in Figure 3. The complexity of the proposed compact *ColGrm* is  $O(m^2/2+m/2)$  during the image retrieval process and storage space but is  $O(m^2d)$  during the feature extraction process because all distances must first be computed prior to the average. Feature extraction is an offline process, which means that extraction is performed once and the feature vectors can be saved in a database ready for the online retrieval process. Therefore, the speed of the interactive process with the user is not significantly affected.

IV. THE ADAPTED DC-BASED CORRELOGRAM DESCRIPTOR

DC-based approaches are introduced to solve the perceptual problem of the conventional color-based approaches by simulating human color perception. One of the most promising DC-based approaches is the method proposed by S. Kiranyaz et al. [4], which integrates DCs with *ColGrm* to solve the problems of both methods. These problems include the lack of the spatial colors information problem of the DC-based approaches and the infeasibility problem of the original *ColGrm* descriptor, especially in large databases. The method is called perceptual correlogram. The DCs are extracted from an image through a method similar to [18], which simulates human color perception. Then, these DCs are back-projected on the image to extract the color correlogram that depends on the DCs. This method proposes a trio-model to measure the dissimilarity of the two images, as depicted in (2) [4].

$$P_{trio}(Q, I) = P_{\phi}(Q, I) + (\alpha P_G(Q, I) + (1 - \alpha)P_{Corr}(Q, I)). \quad (2)$$

The trio-model has three measuring metrics:  $P_{\phi}$ ,  $P_G$ , and  $P_{Corr}$ . The first metric ( $P_{\phi}$ ) measures the mismatching colors and their percentages in the two compared images, as depicted in (3) [4].  $W_i$  and  $C_i$  represent the percentages and the colors values in the mismatching color list ( $S^{\phi}$ ). The other two metrics ( $P_G$  and  $P_{Corr}$ ) measure the difference between the matched colors of the two images.  $P_G$  measures the global difference between the two images, as expressed in (4) [4].  $Nm$  represents the number of matching colors of the two images;  $T_s$  represents color similarity threshold, and  $\beta$  is the value between 0 and 1, which represents the adjustment between the two terms of (4).  $P_{Corr}$  measures the spatial (or *ColGrm*) difference between the two images, as shown in (5) [4], where MC represents a list of similar (matched) colors between the two images Q and I.  $\gamma_{ci,cj}^{(k)}$  is the probability of finding DC  $C_i$  at a distance  $k$  from DC  $C_j$ .

$$P_{\phi}(Q, I) = \frac{\sum (W_i | C_i \in S^{\phi})}{2} \leq 1 \quad (3)$$

$$P_G(Q, I) = \beta \sum_{i=1}^{Nm} |W_i^Q - W_i^I| + (1 - \beta) \sqrt{\frac{\sum_{i=1}^{Nm} (C_i^Q - C_i^I)^2}{T_s N_m}} \leq 1 \quad (4)$$

$$P_{Corr}(Q, I) = \sum_{i,j \in MC} \sum_{k=1}^d \begin{cases} 0 & \text{if } \gamma_{ci,cj}^{(k)}(Q) = \gamma_{ci,cj}^{(k)}(I) = 0 \\ \frac{|\gamma_{ci,cj}^{(k)}(Q) - \gamma_{ci,cj}^{(k)}(I)|}{\gamma_{ci,cj}^{(k)}(Q) + \gamma_{ci,cj}^{(k)}(I)} & \text{else} \end{cases} \quad (5)$$

In other words,  $P_{\phi}$  and  $P_G$  measure the global differences, and  $P_{Corr}$  measures the spatial differences between the compared images. A proper critical analysis of the trio-model reveals serious drawbacks. The first drawback occurs in computing the *ColGrm* dissimilarity metric ( $P_{Corr}$ ), and the second drawback lies in existence of the  $P_G$  and  $P_{\phi}$  that compute general dissimilarity and represent a different perspective from *ColGrm* dissimilarity. The limitation of  $P_{Corr}$  in (5) is identified through a comparison with the dissimilarity measure of the original *ColGrm*, as shown in (2). The results of both dissimilarity measures are compared in Table I.

The similarity measure of the method proposed [4] has a serious problem, which is the lack of discrimination of the dissimilarity measure between large and small differences of the probability values because the dissimilarity values of large differences are equal to those of small differences (as depicted in the fourth column of Table I). This matter is contrary to human visual perception because the human eye cannot recognize small differences. The original *ColGrm* dissimilarity keeps these differences linear. If the difference is large, the dissimilar value is also large; and if it is small, the result is also small.

TABLE I. COMPARISON BETWEEN TWO DISSIMILARITY MEASURE METHODS FOR THE ORIGINAL COLGRM (THIRD COLUMN) AND FOR THE PERCEPTUAL COLGRM 4 (FOURTH COLUMN) TO SHOW THE DRAWBACKS OF THE LATTER.

x	y	$\frac{ x - y }{(1+x+y)}$	$\frac{ x - y }{(x + y)}$	Difference Amount
0	0	0	0	Zero (Equal)
0.5	0.5	0	0	Zero (Equal)
0.5	0	0.333	1	Large
0.005	0	0.005	1	Small
0.5	0.1	0.25	0.66	Large
0.005	0.001	0.004	0.66	Small
0.5	0.4	0.05	0.11	Large
0.005	0.004	0.001	0.11	Small

The dissimilar value of the perceptual descriptor is illogical because even a small difference obtains a large dissimilar value (reaching to 1), and an image may have many small colors. The other metrics (i.e.,  $P_{\phi}$  and  $P_G$ ) in the dissimilarity measure also have values based on the percentages of colors (from 0 to 1), which conflicts with  $P_{Corr}$  that has a value fixed in both the large and small percentages



of color. Therefore, the dissimilarity measure of the original *ColGrm* is better than that of the perceptual *ColGrm* [4]. The original *ColGrm* has a fixed color space, whereas the perceptual *ColGrm* has a dynamic and variable number of colors.

In other words, computing  $P_\emptyset$  and  $P_G$  (global differences) with  $P_{Corr}$  (spatial difference) is unsuitable because of the difference in values and perspective. In the perceptual *ColGrm*, Kiranyaz et al. was forced to use the two together because the  $P_{Corr}$  metric computes the dissimilarity of the matched colors only, whereas the original *ColGrm* dissimilarity measure equation computes the dissimilar values for matched and mismatched colors together. Therefore, the concept of original *ColGrm* can be applied to the adapted DC-based *ColGrm*, which computes the matched and mismatched colors in the same metric. The probability values of the matched colors between the two images in the adapted method will be directly compared because the mismatched colors for each of the two images will be compared with zeros, as in (8).

The corresponding probability values of the mismatching colors in the adapted *ColGrm* can be considered as zeros similar to those in the original *ColGrm*. The original *ColGrm* is simulated and can be considered the second term aside from  $P_{Corr}$ . The proposed duo-model of the adapted DCBC is expressed as follows:

$$P_{duo}(Q, I) = P_{match}(Q, I) + P_{mismatch}(Q, I) \quad (6)$$

$$P_{match}(Q, I) = \begin{cases} \sum_{i,j \in MC} \sum_{k=1}^d \frac{|\gamma_{ci,cj}^{(k)}(Q) - \gamma_{ci,cj}^{(k)}(I)|}{1 + \gamma_{ci,cj}^{(k)}(Q) + \gamma_{ci,cj}^{(k)}(I)} * a_{i,j} & \text{if } i=j \\ \sum_{i,j \in MC} \sum_{k=1}^d \frac{|\gamma_{ci,cj}^{(k)}(Q) - \gamma_{ci,cj}^{(k)}(I)|}{1 + \gamma_{ci,cj}^{(k)}(Q) + \gamma_{ci,cj}^{(k)}(I)} & \text{if } i \neq j \end{cases} \quad (7)$$

$$P_{mismatch}(Q, I) = \sum_{i,j \in Q\_MMC} \sum_{k=1}^d \frac{|\gamma_{ci,cj}^{(k)}(Q) - 0|}{1 + \gamma_{ci,cj}^{(k)}(Q) + 0} + \sum_{i,j \in I\_MMC} \sum_{k=1}^d \frac{|\gamma_{ci,cj}^{(k)}(I) - 0|}{1 + \gamma_{ci,cj}^{(k)}(I) + 0} \quad (8)$$

MC represents the list of the matched colors between the two images Q and I. Q\_MMC and I\_MMC represent the lists of the mismatched colors of images Q and I, respectively. Moreover,  $a_i, j$  represents the similarity ratio between the colors  $C_i$  and  $C_j$ , which can be computed using the following equation [17]:

$$a_{i,j} = \frac{d_{i,j}}{d_{max}} \text{ where } d_{i,j} \leq Tc \quad (9)$$

where  $d_{i,j}$  represents the L1 distance between  $C_i$  and  $C_j$ , and the abbreviation C represents the 3D color values in the CIE-LUV color space, which can be computed as follows [17]:

$$d_{i,j} = |C_i^L - C_j^L| + |C_i^U - C_j^U| + |C_i^V - C_j^V| \quad (10)$$

The color threshold  $Tc$  represents the maximum distance, in which the two colors are considered similar, and is set to 20, and  $d_{max} = \alpha Tc$ ,  $\alpha = 1$ , or 1.2. In (7),  $a_{i,j}$  is multiplied to the *ColGrm* dissimilarity values when  $d \leq 5$ . The reasons behind multiplying only the main diagonal of the *ColGrm*

array by the color similarity ratio ( $a_{i,j}$ ) is that the main diagonal values often represent the percentages of the colors in the image (especially when  $d$  is small) because it contains the probability of finding each color with itself, except for the colors that are too scattered in the image, and is rarely used in images that are converted into images of 8 DCs as the maximum. The other values in the *ColGrm* matrix represent the probabilities of finding a certain color with other colors (spatial correlations). Therefore, multiplying the color similarity ratio with the percentages of the DCs simulates the DC-based approaches to alleviate the problem of non-identical matched colors.

In sum, the differences between the adapted DC-based *ColGrm* descriptor and the perceptual *ColGrm* descriptor lie in two positions. The first difference is that the perceptual descriptor depends on the dissimilarity measure from the different perspectives, with the three metrics measuring the dissimilarity between two images.  $P_\emptyset$  and  $P_G$  are used to measure the global differences of colors. These metrics are produced from the approach perspective of DC.  $P_{Corr}$  measures the spatial correlations of the matched colors only between the two images. This metric represents the *ColGrm* perspective. Combining different perspective metrics may lead to the inconsistency of these metrics, which may produce an inaccurate dissimilarity value. Nevertheless, the adapted DC-based *ColGrm* depends on the *ColGrm* perspective only, which can measure global and spatial color differences together efficiently, making accuracy better than that of the perceptual descriptor (as shown in the experimental results in Section V). The second difference is the dissimilarity measure of the perceptual *ColGrm* descriptor ( $P_{Corr}$ ), which is different from the original metric. The new metric has a serious limitation of being unable to differentiate between large and small probabilities of the correlations of color in the image, as shown in Table I.

## V. EXPERIMENTAL RESULTS

The evaluation of the proposed compact-generalized *ColGrm* descriptor, adapted DC-based *ColGrm* descriptor, and the integration of both is conducted on two datasets: 1) the well-known Corel-10K dataset that contains 80 classes and 10,800 images, with 100 images existing for each class in the dataset; and 2) the Cartoon-11K dataset that contains 11,120 images collected from the web, with 146 classes (cartoon characters) existing, with each one having at least 35 images. The two datasets are used to show the superiority of the proposed color-based descriptors in large databases.

The descriptors selected to be compared with the proposed CGC, adapted DCBC, and the integration of the two are the original *ColGrm* [13][14] (whenever applicable), *AutoCorrelogram* [13], MPEG-7 Dominant Color Descriptor (DCD) [17], and Perceptual *ColGrm* [4]. The rationale for this selection is the representation of the first two descriptors of the original *ColGrm* descriptor, which are considered the base of the proposed descriptors. The third descriptor (DCD) is the base of any DC-based approach, which is used in DCBC. The last descriptor represents the original descriptor, which has been adapted to produce the DCBC descriptor.

### A. Performance Measure Metrics

A quantitative performance measure metrics is utilized to measure the accuracy of the proposed descriptors with the other ColGrm descriptors chosen for comparison. Two of the metrics are the average retrieval rate (ARR) [37] and the average normalized modified retrieval rank (ANMRR) [17][37]. These metrics are used by the MPEG-7 committee to evaluate its work and are considered two of the most widely used metrics. These metrics combine many conventional metrics, including hit–miss counters, precision–recall, and ranking information, and they represent all-in-one value. The third metric is the mean average precision (MAP), which is one of the most widely used metrics in CBIR and is a compromise between precision and recall in a single metric [32][38]. This metric has become one of the leading performance evaluation metrics in ad hoc retrieval systems [38]. The fourth metric is P(10), which is a precision value of the first 10 retrieved images by a specific query. This metric is the most widely used metric for web-based image retrieval [32], as the user tends to see the result of his query in the first page or prefer to reformulate the query instead of checking the second page. The best value for the metrics ARR, P(10), and MAP is close to 1, indicating that the relevant images are retrieved in good standing. The best value of ANMRR is close to 0. MAP differs from ANMRR in that MAP measures the retrieval accuracy to all relevant images in the database to a particular query, whereas ANMRR measures the retrieval accuracy within a specific window (W) size. The window size is normally equal to twofold of the ground truth size of a specific image query.

The complexity of the proposed descriptors, in terms of time and memory space, is also urgently computed as the fifth metric to prove their applicability in large databases. The applicability of the proposed descriptors in large databases is the main aim of this study. The accuracy metrics are used to prove that the compactness of the proposed descriptors does not significantly degrade performance.

### B. Retrieval Performance

The retrieval performance of the competing descriptors in the specified datasets can be measured using the accuracy and complexity metrics. The complexity metrics represent the computing time and memory space needed for the comparison of the proposed descriptors with the competing descriptors. Time is divided into feature extraction time (offline) and image retrieval time (online). Memory space is referred to as the main memory or disk space required by the descriptors. The diversity of queries is also important in ensuring fair and honest results [38]; thus, the evaluation queries are selected from all classes of the databases.

#### 1) Retrieval performance of the Corel-10K dataset

An experiment is conducted on the Corel-10K dataset [40] with 111 queries. The results of the four evaluation metrics and the complexity of the memory space are given in Tables II and III, respectively, to show the accuracy and efficiency of the proposed methods compared with other descriptors. A single value in the “MPEG7 DCD” column in Table II indicates that this descriptor does not have a

different setting of distances to compute unlike other descriptors. The percentages of colors are depended upon rather than the distances among colors, which are used in spatial ColGrm methods. The left part of Table II (i.e., the first three columns) shows that the best accuracy values are those of the original ColGrm, which are better than proposed CGC. However, the values are applicable only for minimum settings ( $3 \times 3 \times 3$  colors of each band and distances equal to 5 and 10), as shown in Tables II and V. The slight degradation of the accuracy of the proposed descriptor is caused by the generalization of the distances that loses the values of the accurate distances. A comparison is then made by increasing the setting, such as  $4 \times 4 \times 4$  colors and 5, 10, and 40 distances. Only the Autocorrelogram and the proposed CGC can be applied in this case. The proposed descriptor also outperforms the Autocorrelogram because of the preservation of the spatial correlation of each image color with other colors, whereas the Autocorrelogram has a spatial correlation of each color with itself and ignores the others. In the ColGrm descriptors, the accuracy is decreased when the number of distances is increased because the unsuitable distances will have an effect on the suitable distances, which is a certain distance indicating that the actual distance between the specific color and the other colors in the image exists. The memory space and image retrieval time remain  $O(m^2/2+m/2)$ , which are online processes (performed when comparing the query image ColGrm with all database images of the ColGrms), despite the increase in the distances of the proposed descriptor. This increase in distances only affects the feature extraction process, which is an offline process (performed once only when creating the database away from an interaction with users), and the extraction query image ColGrm, in which the complexity of its computation and memory space is  $O(m^2d)$  and is equal to the original correlogram.

The middle part of Table II (i.e., second three columns) shows that the adapted DCBC outperforms the three original descriptors (i.e., DCD, ColGrm, and the perceptual ColGr). The adapted descriptor is more accurate than the original version [4] because the latter has many drawbacks, as mentioned in Section IV. The complexity of the perceptual and proposed DCBC descriptors is  $O(8^2d)$  as the maximum, where 8 represents the maximum DCs that can be extracted from the image. The significant degradation accuracy of the perceptual descriptor when increasing the distance is also noticeable because the incompatibility between the spatial dissimilarity ( $P_{Corr}$ ) and global dissimilarity ( $P_\emptyset$  and  $P_G$ ) when increasing the distance leads to the significant change in the  $P_{Corr}$ . The global dissimilarity values (i.e.,  $P_\emptyset$  and  $P_G$ ) remain unchanged. The dissimilarity measure of the perceptual ColGrm descriptor has a serious limitation. The integration of the proposed methods is achieved by applying the compactness and generalization concepts of the CGC (first proposed descriptor) on the DC-based ColGrm (second adapted descriptor). The combination outperforms

all three original descriptors (i.e., MPEG-7 DCD, *ColGrm*, and Perceptual *ColGrm*), with a maximum complexity of  $O(8^2/2+8/2) = O(36)$ .

The single value in an entire row in Table III indicates that either the descriptor does not have different distances in its computations (e.g., MPEG7 DCD) or that the descriptor produces the same memory space for all distances (e.g., the proposed CGC and the integration of CGC and DCBC). Tables II and III show that the integration of CGC and DCBC is a promising approach to the minimal consumption not only of memory space but also of image retrieval time.

Increasing the setting of *ColGrm* to four colors for each band ( $4 \times 4 \times 4 = 64$  colors) leads to the proposed CGC outperforming all the other competing DC-based descriptors. This result is caused by the variety of colors (64 in CGC) being higher than that of the DC-based *ColGrm* approaches (8 colors maximum).

Table V clearly shows that the original color correlogram is inapplicable in a setting with 64 ( $4 \times 4 \times 4$ ) colors. The original color correlogram has serious limitations, such as high computational complexity and memory storage (Table IV). Only the *Autocorrelogram* and all the compact descriptors can be applied. The proposed descriptors and their integration also outperform the *Autocorrelogram* and the perceptual *ColGrm*. The perceptual *ColGrm* appears worse than the *Autocorrelogram* because of the aforementioned limitations shown in Tables II and V. The key contribution of this paper is solving the feasibility problems (in computations and memory space) of the original *ColGrm*. Increasing the setting to more than four colors in each band is not shown in this paper because the results are similar to those of the setting of four colors.

## 2) Retrieval performance of the Cartoon-11K dataset

The four evaluation metrics are computed for the 158 queries on the Cartoon-11K dataset (this database is collected from Google and will be published soon) in Tables VI and VII, respectively, to show the accuracy of the proposed methods compared with other descriptors.

Table VI shows that the adapted DCBC descriptor outperforms all competing descriptors, including the perceptual descriptor. The proposed descriptor CGC shows the same accuracy as the original *ColGrm* but with a significant reduction in complexity  $O(m^2d)$  to  $O(m^2/2+m/2)$ .

Table VII, with a setting of four colors, shows that the proposed CGC outperforms the adapted DCBC because the abundance of the colors can be expressed on the image content more efficiently than DCs. The storage space required for the Cartoon database is approximately equal to that in the Corel database, as depicted in Tables III and IV. These tables show that the compactness of the proposed, adapted, and integrated descriptors increases the speed of the image retrieval process.

## VI. CONCLUSION

In this paper, two compact correlogram descriptors are proposed for large databases. The first descriptor, CGC, solves the inapplicability problems of the color correlogram in large databases. CGC reduces the colors of *ColGrm* approximately by half and performs a generalization of all the distances into a single representative distance. This descriptor also has less degradation accuracy than the original *ColGrm*, but the latter cannot be applied in a large setting with increased colors, distances, or database sizes. CGC also outperforms the *Autocorrelogram*, which can be applied in large settings, because the proposed method keeps the correlations of each color in the image with other colors, whereas the *Autocorrelogram* keeps the correlations of each color only with itself and ignores the relations with other colors. The second descriptor is the DC-based *ColGrm* adapted from the perceptual *ColGrm* [4], which suffers from serious limitations in its dissimilarity measure. DCs offer both perceptual and compact descriptions of colors. Therefore, the combination of DCs with *ColGrm* surpasses all the competing descriptors in terms of accuracy, time, and storage space. Integrating the proposed descriptors also shows promising results in significantly reducing complexity.

TABLE II. ANMRR, ARR, P(10), AND MAP VALUES FOR ALL COMPETING DESCRIPTORS ON COREL-10K DATABASE WITH 111 QUERIES (WITH NO. OF COLORS EQUALS  $3 \times 3 \times 3 = 27$  COLORS AND DISTANCE = 5, 10, AND 40). BEST ACCURACY VALUES ARE IN BOLD.

Descriptor Metric	Original Correlogram	Auto-Correlogram	Proposed CGC	MPEG-7 DCD	Perceptual CG	Adapted DCBC	Integration CGC+DCBC
ANMRR	0.646/651/NA	0.705/714/739	0.648/659/680	0.710	0.688/779/935	<b>0.591/595/605</b>	0.600/612/632
RR	0.287/280/NA	0.240/233/208	0.285/278/258	0.235	0.250/188/052	<b>0.337/334/326</b>	0.328/325/301
P(10)	0.57/.55/NA	0.43/.42/.41	0.57/.55/.51	0.40	0.50/.37/.21	<b>0.62/.62/.60</b>	0.60/.60/.57
MAP	0.294/285/NA	0.232/225/200	0.293/283/257	0.206	0.241/166/042	<b>0.328/324/317</b>	0.317/311/290
Average	0.376/366/NA	0.299/291/269	0.375/363/269	0.282	0.325/236/092	<b>0.423/420/409</b>	0.411/406/382



TABLE III. SIZE OF THE FEATURES' DATABASE FOR COREL-10K AND COLORS IS (3 × 3 × 3) 27 FOR ALL COMPETING DESCRIPTORS.

ColGrm Method	Distance=5	Distance=10	Distance=40
<b>Original ColGrm</b>	278.1 M	556.2 M	2.17 G
<b>AutoCorrelogram</b>	10.3 M	20.6 M	82.4 M
<b>Proposed CGC</b>		28.8 M	
<b>MPEG7 DCD</b>		0.85 M	
<b>Conceptual ColGrm</b>	25.2 M	49.7 M	196.1 M
<b>Proposed DCBC</b>	25.2 M	49.7 M	196.1 M
<b>Integration of CGC+DCBC</b>		3.6 M	

TABLE V. ANMRR, ARR, P(10), AND MAP VALUES FOR ALL COMPETING DESCRIPTORS ON **COREL-10K DATABASE** WITH 111 QUERIES (WITH NO. OF COLORS EQUALS 4 × 4 × 4 = 64 COLORS AND DISTANCE = 5,10, AND 40). BEST ACCURACY VALUES ARE IN BOLD.

Descriptor Metric	Original Correlogram	Auto-Correlogram	Proposed CGC	MPEG-7 DCD	Perceptual CG	Adapted DCBC	Integration CGC+DCBC
<b>ANMRR</b>	N/A	0.619/650/661	<b>0.552/559/580</b>	0.710	0.688/779/935	0.591/595/605	0.600/612/632
<b>RR</b>	N/A	0.317/305/298	<b>0.377/367/358</b>	0.235	0.250/188/052	0.337/334/326	0.328/325/301
<b>P(10)</b>	N/A	0.53/.52/.51	<b>0.64/.62/.61</b>	0.40	0.50/.37/.21	0.62/.62/.60	0.60/.60/.57
<b>MAP</b>	N/A	0.323/315/300	<b>0.387/380/357</b>	0.206	0.241/166/042	0.328/324/317	0.317/311/290
<b>Average</b>	N/A	0.387/372/361	<b>0.463/453/444</b>	0.282	0.325/236/092	0.423/420/409	0.411/406/382

TABLE VI. ANMRR, ARR, P(10), AND MAP VALUES FOR ALL COMPETING DESCRIPTORS ON **CARTOON-11K DATABASE** WITH 158 QUERIES (WITH NO. OF COLORS EQUALS 3 × 3 × 3 = 27 COLORS AND DISTANCE = 5,10, AND 40). BEST ACCURACY VALUES ARE IN BOLD.

Descriptor Metric	Original Correlogram	Auto-Correlogram	Proposed CGC	MPEG-7 DCD	Perceptual CG	Adapted DCBC	Integration CGC+DCBC
<b>ANMRR</b>	0.853/0.853/NA	0.880/890/902	0.853/854/855	0.945	0.927/944/969	<b>0.838/838/839</b>	0.841/844/851
<b>ARR</b>	0.118/117/NA	0.094/088/077	0.117/117/116	0.041	0.057/041/023	<b>0.130/130/130</b>	0.126/123/117
<b>P(10)</b>	0.35/.35/NA	0.29/.26/.24	0.35/.35/.35	0.08	0.20/.17/.10	<b>0.39/.38/.39</b>	0.37/.37/.36
<b>MAP</b>	0.098/097/NA	0.075/069/060	0.097/097/097	0.029	0.045/038/023	<b>0.105/105/104</b>	0.102/098/094
<b>Average</b>	0.178/.177/NA	0.144/131/118	0.177/177/176	0.051	0.093/076/044	<b>0.194/194/194</b>	0.189/186/180

TABLE VII. ANMRR, ARR, P(10), AND MAP VALUES FOR ALL COMPETING DESCRIPTORS ON **CARTOON-11K DATABASE** WITH 158 QUERIES (WITH NO. OF COLORS EQUALS 4 × 4 × 4 = 64 COLORS AND DISTANCE=5,10, AND 40). BEST ACCURACY VALUES ARE IN BOLD.

Descriptor Metric	Original Correlogram	Auto-Correlogram	Proposed CGC	MPEG-7 DCD	Perceptual CG	Adapted DCBC	Integration CGC+DCBC
<b>ANMRR</b>	N/A	0.867/870/892	<b>0.830/833/835</b>	0.945	0.927/944/969	0.838/838/839	0.841/844/851
<b>ARR</b>	N/A	0.107/100/089	<b>0.136/135/133</b>	0.041	0.057/041/023	0.130/130/130	0.126/123/117
<b>P(10)</b>	N/A	0.32/.28/.25	<b>0.41/.40/.38</b>	0.08	0.20/.17/.10	0.39/38/39	0.37/.37/.36
<b>MAP</b>	N/A	0.083/079/070	<b>0.114/110/108</b>	0.029	0.045/038/023	0.105/105/104	0.102/098/094
<b>Average</b>	N/A	0.160/147/129	<b>0.208/203/196</b>	0.051	0.093/076/044	0.194/194/194	0.189/186/180

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TABLE IV. SIZE OF THE FEATURES' DATABASE FOR COREL-10K AND COLORS IS (4 × 4 × 4) 64 FOR ALL COMPETING DESCRIPTORS.

ColGrm Method	Distance=5	Distance=10	Distance=40
<b>Original ColGrm</b>	1.52 G	3.1 G	12.2 G
<b>AutoCorrelogram</b>	24.4 M	48.8 M	195.3 M
<b>Proposed CGC</b>		158.7 M	
<b>MPEG7 DCD</b>		0.85 M	
<b>Conceptual ColGrm</b>	25.2 M	49.7 M	196.1 M
<b>Proposed DCBC</b>	25.2 M	49.7 M	196.1 M
<b>Integration of CGC+DCBC</b>		3.6 M	

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