Improving the Effectiveness of the Color Coherence Vector

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Abstract: *This paper was motivated by the desire to improve the effectiveness of retrieving images on the basis of their color content by improving the Color Coherence Vector method. There is a growing demand for efficient and effective image retrieving techniques from the huge multimedia databases on the Internet and from the image libraries. In this paper three methods have been proposed and developed to improve the effectiveness of the Color Coherence Vector method: The modified Color Coherence Vector based on the number of the color coherence regions, The modified Color Coherence Vector based on the distance of the color coherence regions and The modified Color Coherence Vector based on the angle of the color coherence regions. The proposed methods take advantage of the coherence regions number and location information. The information of the coherence regions number, distance and angle along with the coherence and incoherence pixels amount for each color was presented by using the simple and flexible histogram representation technique. The experiments were carried out on a collection of 1014 color images of which 100 query images were used as stimuli for retrieving similar images from the image collection. The experimental results indicate that the three proposed methods perform better than Color Coherence Vector in terms of retrieval effectiveness; the developed methods produce better recall-precision curves and produce better ordering values in terms of E_{avg} (Ratio (average-rank to ideal-average-rank)). These results provide evidence for the importance of the coherence regions number and location information which have been neglected by the original method color coherence vector.*

Keywords: *Content-based image retrieval, color coherence vector, color-based image retrieval, and color indexing.*

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1. Introduction

Image retrieving is a very important area of research that should satisfy efficient retrieving and effective retrieval of images from databases. This is due to the growing desire of retrieving certain images (that satisfy certain features and conditions) from the growing digital image libraries and databases. The importance of Content-Based Image Retrieval (henceforth CBIR) is motivated by the increasing desire for retrieving images from growing digital image databases over the Internet. The CBIR is fast, efficient and can automatically extract low-level features (such as color) from images to assess the similarity between different images. The research aims to improve the effectiveness of retrieving images on the basis of their color content by improving the Color Coherence Vector (CCV) method developed by Pass *et al.* [6].

2. Statement of the Problem

The CCV method [6] is a refined method of the color histogram method. The CCV takes into account some of the spatial information between the pixels within the same color coherence region. The idea of improving the effectiveness of the CCV method depends on the researcher's opinion of the importance of the location and/or the number of the significant-sized colored region in discriminating between images. To understand the importance of the numbers of the significant-sized colored region see Figure 1, which is similar to the figure used by Huang et al to explain the difference between the CCV and the autocorrelograms [1]. There are two images on the left of Figure 1 each of which has (121 pixels), the size threshold of the coherence region is set to 1% of the image size, that means the number of pixels in the coherence region for image A or B should be at least equal to two pixels.

The two images A and B have the same CCV color feature vector as shown in Figure 1, because the amount of the coherence pixels in image A is the same as the amount of coherence pixels in image B. This is also true for incoherence pixels in the two images (there are no incoherence pixels in Figure 1). We notice that there is a problem in the CCV method because it doesn't tell us about the existence of dissimilarity between image A and image B in Figure 1.

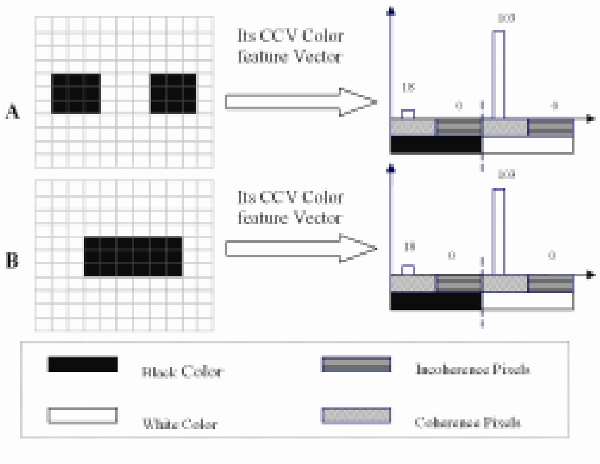

Figure 1. Two images and their CCV color feature vectors.

To solve the previous problem we can compare the number of coherence regions of the same color between the two images. As we see, the number of coherence regions shows us that there is a difference between the two images and this could improve the effectiveness of retrieval. In contrast consider the other set of different images where the number of coherence regions will not play any role in discriminating between the images. Figure 2 shows us this situation. All of the three images in Figure 2 have the same CCV color feature vector and also the same number of coherence regions (each image has two black coherence regions and one white coherence region) although they differ in appearance. The solution for this kind of situation is to compare these different images by comparing the location of coherence regions of the same color between different images.

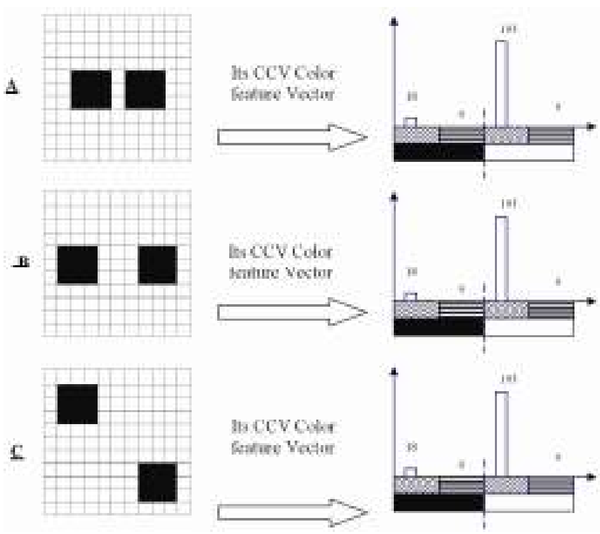

Figure 2. Three images and their CCV color feature vectors.

3. Suggested Solution

This research proposed new methods (CCV_N, CCV_D and CCV_A) that take advantages of the coherence regions numbers and locations information. The coherence regions location and number were represented by using the histogram representation technique which is simple and flexible. The histogram representation provides us with the ability to retrieve images by any type of information either singly or by combining different types of coherence regions information.

3.1. The Proposed Methods

The following two subsections will explain the methodology that will be used to produce the vectors of the proposed methods based on the location and the number of coherence regions.

3.1.1. The Modified Color Coherence Vectors Based on the Locations of the Color Coherence Regions

The location of the color coherence region will be determined by using the bounding box method and the Polar Coordinates. There could be different viewpoints that determine the location of the origin point. In this research we will choose the center of the image to be the origin point because we want the distance information of the coherence regions to remain unchanged when the image is rotated. In the other hand, the angle information will be changed when the image is rotated. For example Figure 3 shows us an image with two gray coherence regions and the process of determining the location of its coherence regions from the center of the image.

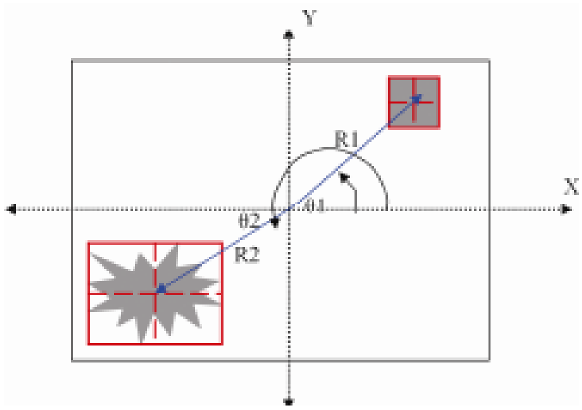

Figure 3. The process of determining the location of two gray coherence regions.

To represent the location information in a histogram we will need two bins for each color. One bin for the distances of the coherence regions from the center of the image and the other bin for the angles information of the coherence regions from positive horizontal axis. For example in Figure 4 there is an image with two black coherence regions and a big white coherence region (we suppose that the coherence size threshold is equal to or larger than two pixels) .

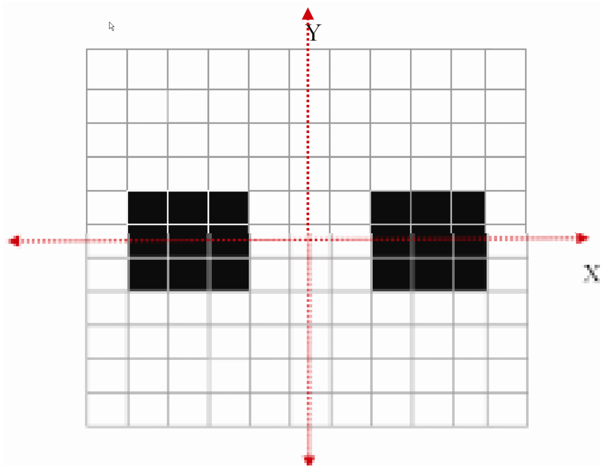

Figure 4. Simple image with two black coherence regions and one white coherence region.

The center of the bounding box for the black region on the left is (-3, 0) and for the other black region to the right is (3, 0), and the center of the bounding box for the big white coherence region is (0, 0). To convert the coordinates of the coherence region centers from Cartesian to Polar we use the equations 1 and 2. Table 1 shows us the final results:-

Table 1. The coherence region locations in Cartesian and polar coordinates.

Cartesian Coordinates	Equations 1 and 2	Polar Coordinates
(3, 0)	$R = \sqrt{x^2 + y^2}$	3<0
(-3, 0)		3<180
(0, 0)	$\theta = \tan^{-1}\left(\frac{y}{x}\right)$	0<0

Each location value consist of two numbers, one for the distance (R) and the other for the angle (θ). From Figure 4 and Table 1, it can be seen that there are two location values for the black color. The distance bin for the black color in the histogram can contain only one number value. Because we have two distance values for the black color we will use the summation of these two values. The same procedure will be done for the angle values. For simplicity and efficiency reasons, we will represent the information of the coherence region locations by using two vectors. The first vector will contain the size bins CCV and the distance bins. The method of using this vector for retrieving will henceforth be denoted by CCV_D. The second vector will contain the size bins CCV and the angle bins. The method of using this vector for retrieving will henceforth be denoted by CCV_A.

1. The Color Feature Vector for the CCV_D Method To represent the distance information of coherence regions in a histogram we will need one bin for each color beside the two size bins of coherence and incoherence. For example, the modified Color Coherence Vector based on the distance information of the color coherence regions for the image in Figure 4 after the calculations will be as shown in Figure 5.

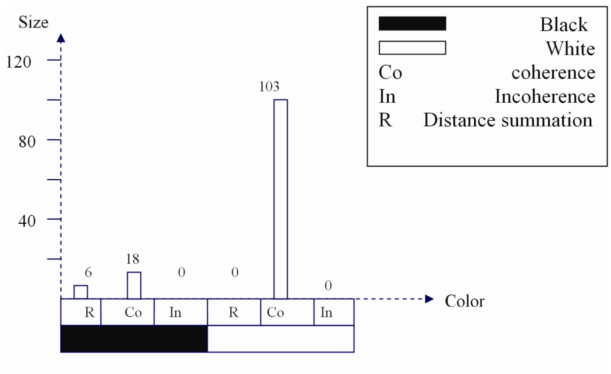

Figure 5. CCV_D feature vector for the image in Figure 4.

2. The Color Feature Vector for the CCV_A Method. To represent the angle information of coherence regions in a histogram we will need one bin for each color beside the two size bins of coherence and incoherence. For example, the modified CCV based on the angle information of the color coherence regions for the image in Figure 4 after the calculations will be as shown in Figure 6.

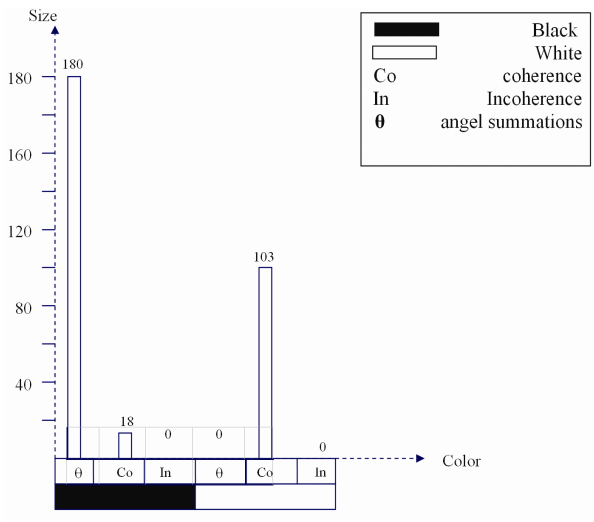

Figure 6. CCV_A feature vector for the image in Figure 4.

3.1.2. The Modified Color Coherence Vector Based on the Number of the Color Coherence Regions

To represent the number of coherence regions in a histogram we will need one bin for each color beside the two size bins of coherence and incoherence. For example, in Figure 4 there are two black coherence regions and one white coherence region. After the calculations, the modified Color Coherence Vector based on the numbers of the color coherence regions for the image in Figure 4 will be as shown in Figure 7. This method will henceforth be denoted by CCV_N.

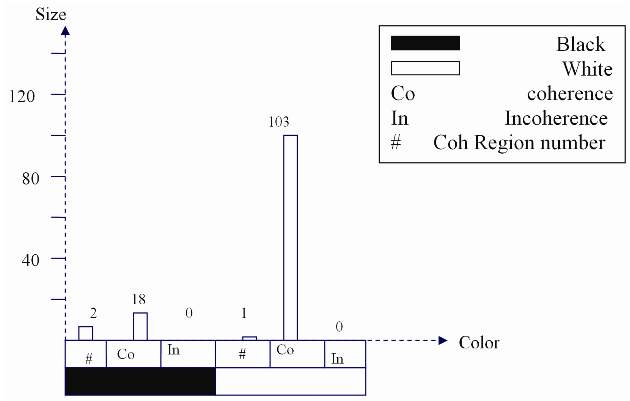

Figure 7. CCV_N feature vector for the image in Figure 4.

3.2. Normalization

The normalization process is a transformation process of a value into a range of 0 and 1. For example, given a variable X whose value range is between D_{max} and D_{min}, where D_{max} and D_{min} are known, the normalization can be done by the equation.

$$\delta = \frac{X - D_{min}}{D_{max} - D_{min}}$$

In the previous equation if the value of the variable X is always equal to or greater than zero, then we can normalize the value of X by using the equation.

$$\delta = \frac{X}{D_{max}}$$

The procedures of normalization the feature vectors of the proposed methods are as follows:

- The normalization of the size values can be achieved by dividing the coherence and incoherence size bins by the size of the image.
- The normalization of the coherence regions number bins can be achieved by dividing each region's number bin by the maximum number of coherence regions. To calculate the maximum number of coherence regions we should divide the image size by the coherence size threshold value.
- The maximum distance for a point from the center of the image is when it is located at one of the image corners. There could be more than one coherence region in an image, each of which has one point that represents its center location. We can calculate the maximum distance value for all possible coherence regions by multiplying the maximum number of coherence regions by maximum distance value for a point from the center of the image. The normalization of the coherence regions distance bins can be achieved by dividing each regions distance bin by the maximum distance value for all possible coherence regions.
- The maximum angle value for a point from the positive horizontal axis is 359^o. When multiplying the maximum angle value by the maximum possible number of coherence regions we will get the maximum angle value for the all possible coherence regions. The maximum angle value for all possible coherence regions will be used to normalize the coherence regions angle bins in the CCV_A vector.

4. Experimental Results

In this section, we evaluate the proposed methods (CCV_N , CCV_D and CCV_A) with respect to the following parameters:

1. The Coherence size threshold.
2. The weight factors of the coherence-incoherence pixels size , coherence regions number, coherence regions distance and coherence regions angle.

The distance between the image features will be determined by using the Euclidean Distance. We will also merge the different similarity values on the basis of weight factors to be empirically determined. We also compare the effectiveness of the CCV method, with the new proposed methods (CCV_N, CCV_D and CCV_A).

4.1. Experiment Setup

The effectiveness of retrieval was evaluated by using WANG image database in addition to 14 adapted from them such that the total of the images used was 1014. WANG image database is a subset of 1000 images of the corel image database which were selected manually to form 10 categories; each category contains 100 relevant images, see Table 2. The images are in RGB color model with resolution (72 pixels/inch) and they are stored in JPEG format with size 384 X 256 or 256 X 384.

Table 2. Image database categories.

Image Name	Category Name
0-99	Africa people and villages
100-199	Beach
200-299	Buildings
300-399	Buses
400-499	Dinosaurs
500-599	Elephants
600-699	Flowers
700-799	Horses
800-899	Mountains and glaciers
900-999	Food

We used two sets of images from the used image database to evaluate the proposed methods. The first image set consists of 60 images selected randomly, six images per category. Every image in the first set will be used as an example to retrieve the image that are similar to it in the image database. The first image set is used for two objectives:

1. To determine the best weight factors that give the best retrieval effectiveness when merging between the size and the other information types (distance, angle and number of coherence regions).
2. To show the effectiveness of retrieval for all the methods (CCV, CCV_N, CCV_D and CCV_A) on the best weight factors which are determined by the first objective.

The second image set is divided into 8 groups of images. Each group consists of 5 highly relevant images. Most images in each group are selected manually from the used image database on the basis of their highly similar visual appearance (each group contains images for the same scene with different viewing positions). When the used image database does not contain the complete number of high relevant images (5 images) for each group, an image is selected from each incomplete group and manipulated by Adobe Photoshop software and saved with a new name to complete the number of images in each group. This operation will produce fourteen new images whose names are: 7_crop.jpg, 7_crop_rot.jpg, 7_L7.jpg, 40_Sc170.jpg, 46_crop1.jpg, 46_L18.jpg, 46_r90.jpg, 242_L8.jpg, 278_Crop1.jpg, 278_Crop2.jpg, 279_L4.jpg, 284_crop1.jpg, 298_rot.jpg and 299_Sc130.jpg, see Appendix (A) for details description about these images. Thus the total number of images in the database becomes 1014. The manipulation techniques that are used for the manipulated images are:

1. Cropping images.
2. Rotation images.
3. Resizing images.
4. Lighting images.

The images of the first image set are shown in Appendix (B), and the images of the second image set are shown in Appendix (C).

4.2. Evaluating Effectiveness

4.2.1. Precision and Recall Metrics

The standard and popular way of evaluating the information retrieval is by using the precision and recall metrics [7, 10]. Precision indicates the proportion of the retrieved images that are relevant to the query image, and the Recall is the proportion of the relevant images in the database that are retrieved in response to a query image [7]. The recall and the precision values are given by using the following two formulas:

$$\mathrm{Pr}\,ecision = \frac{the\ number\ of\ retrieved\ images\ that\ are\ relevant}{the\ number\ of\ retrieved\ images}$$

$$\mathrm{Re}\,call = \frac{the\ number\ of\ retrieved\ images\ that\ are\ relevant}{the\ total\ number\ of\ retrieved\ images}$$

A Precision-Recall curve is used widely by different researchers to show the retrieval effectiveness of the CBIR techniques. The curve with maximum precision and recall values indicates the best effectiveness; i.e. the curve that is closest to the upper–right hand corner indicates the best effectiveness [10]. We can plot a Precision-Recall curve by using a set of ordered recall and precision values to represent the different levels of retrieving. Each recall and precision value at any level is calculated by using the average recall and precision values for a group of images at the same level. In this paper we plotted the Precision-Recall curve based on a set of 20 ordered recall and precision values. Each recall and precision value in the set represents the average recall and precision values for 60 query images in the first image set.

4.2.2. Image Ranks

The rank of the image represents the position (order) of the image in the retrieved image list. The ranks of the relevant images are used for evaluating the retrieving effectiveness in the domains where some images are more relevant than others in the same relevant category. There are different strategies that use the concept of image ranking for image retrieving evaluation. The following is the formula for the strategy which we will use in this research [10].

$$E = \frac{The\ average\ rank}{The\ ideal\ average\ rank}$$

4.3. Evaluating the Retrieving Methods by Using the Precision and Recall Metrics

In this section the effectiveness of retrieval for the CCV method will be presented. The retrieval effectiveness of the CCV method will be a model of retrieval with which the new methods proposed in this paper will be compared. Four coherence size threshold values for the CCV method have been used, they are: 0.01, 0.003, 0.001 and 0.0003. Table 3 shows the average retrieval precision of the CCV method (on different coherence size threshold values) for the first 8, 16 , 24 , 32 and 40 retrieved images by using the images of the first image set (60 images) as an example to retrieve the images that are similar to it in the image database.

Table 3. The average retrieval precision of the CCV method using the second image query set (60 images).

Technique Name	Average Relevant Images from the First 8 Images	Average Relevant Images from the First 16 Images	Average Relevant Images from the First 24 Images	Average Relevant Images from the First 32 Images	Average Relevant Images from the First 40 Images	Retrieval Precisions Sum
CCV (0.01)	4.983333333	8.95	12.68333333	15.96666667	19.1166667	2.687639
CCV (0.003)	5.1	9.083333333	12.466666667	15.53333333	18.4833333	2.672153
CCV (0.001)	5.15	8.983333333	12.5	15.66666667	18.7166667	2.683542
CCV (0.0003)	5.15	9.166666667	12.61666667	15.9	19	2.714236

The sum column in Table 3 represents the summation of retrieval precision percents for the first 8, 16, 24, 32, and 40 retrieved images. For example, the summation of retrieval precision percents for the first row [CCV (0.01)] was computed by the following calculations:

$$= (4.983333333/8) + (8.95/16) + (12.68333333/24) + (15.96666667/32) + (19.1166667/40) = 2.687639$$

The CCV at threshold (0.0003) which gives the best results will be the base case of retrieval with which the proposed methods will be compared. To assess the relative discrimination power of the CCV method (which contains the size of coherence and incoherence pixels) and the other coherence regions information (which include coherence regions distance, angle and number), we will use a weight factor for each type of information. To evaluate the average precision values of the new proposed methods for the first 8, 16, 24, 32 and 40 retrieved images by using the images of the first image set (60 images), the CCV method will be given a constant weight factor 100%. The other coherence regions information types: Number, Distance and Angle, will be given weights from 0% to 4900%, and the stepping value each time will be 100. The purpose of using high weight values for the Number, Distance and Angle is to increase their roles in discrimination, because their values after the normalization step are very small when compared with the size information. Figure 8 shows that at weight 0 all the new methods have the same precision value of the CCV method. When we increase the weight of Number, Distance and Angle features the precision effectiveness of the new methods also increase.

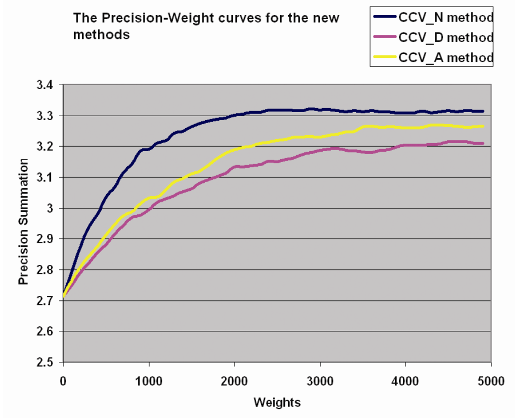

Figure 8. The precision-weight curves for the new methods CCV-N, CCV-D and CCV-A.

For the purpose of comparing the effectiveness of the proposed methods (CCV_N , CCV_D and CCV_A) with the traditional method CCV, the weight factors that yield the best precision results are as shown in Table 4.

Table 4. The weight factors that yield the best average precision values.

Feature Name (Information Type)	The Weight Factor Value that Yields the Best Average Precision Value	The Weight Factor Value that Yields the Best Average Precision Value in Percent
Number of coherence regions	2900%	(2900/300)≈0.967
Distance of coherence regions	4600%	(4600/4700)≈0.978
Angle of coherence regions	4400%	(4400/4500)≈0.977
Size Coh/InCoh pixels	100%	With Number≈0.033 With Distance≈0.022 With Angle≈0.023

Figure 9 shows the Precision-Recall curves for all the methods. The optimal curve is shown at the upper-right hand of the figure. The observer of the figure can see that the curves of the proposed methods are closer to the optimal curve than the CCV method.

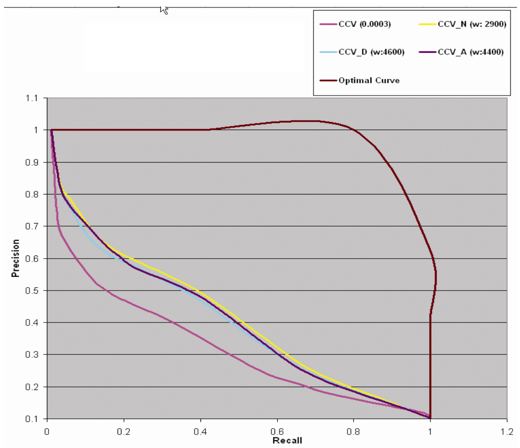

Figure 9. The precision-recall curves for the CCV(0.0003), CCV-N, CCV-D and CCV-A methods.

4.4. Evaluating the Retrieving Methods by Using the Ranks of Retrieved Images

For each group in the second image set, one image is used as a query image and the ranks of the other images in the group are averaged. This process is repeated for each image in the group. The optimal value of E is when its value equal to one. The technique, whose E value is very close to one, is better than the technique whose value is far from one. The final statistical results for all image groups are shown in Table 5.

The Average column in the table shows that the effectiveness of the proposed methods is about two times better than the CCV method. The experiments show that the proposed methods are promising. The proposed methods achieve better retrieval effectiveness, in general, than the CCV method. Moreover, the experiments on the second image set show that the newly proposed methods are effective in general in retrieving highly relevant images when they are rotated, resized, cropped and lighted. For example, Figure 10 shows some query images and the ranks of some of their highly relevant retrieved images by all the mentioned retrieving methods. Figure 11 shows the first 8 retrieved images for all the mentioned methods by using the query image (607.jpg). The observer can notice that the retrieved images at rank 0 are identical to the query image.

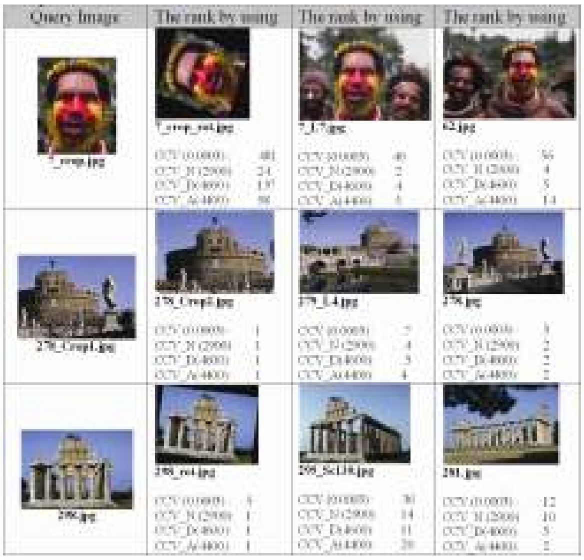

Figure 10. Three query images and the ranks of some highly relevant retrieved images by using CCV, CCV-N, CCV-D and CCV-A.

Figure 11. The first 8 retrieved images for all the methods when the query image is (607.jpg).

5. Efficiency

The color feature vectors for proposed methods (CCV_N, CCV_D and CCV_A methods) are longer than the color feature vectors of CCV method. That means that the proposed methods need more time to produce their color feature vectors, and need longer time than CCV method when the most similar images are retrieved from the database. The cost of producing the feature vectors for all the methods are shown in Table 6.

Table 5. The final statistical results for all image groups in the second image set.

Image Name Technique Name	Group1 E_{avg}	Group2 E_{avg}	Group3 E_{avg}	Group4 E_{avg}	Group5 E_{avg}	Group6 E_{avg}	Group7 E_{avg}	Group8 E_{avg}	Average
CCV Threshold (0.0003)	128.86	9.06	30.94	81.26	74	14.86	7.28	70.26	52.065
CCV_N Threshold (0.0003) Weight (2900)	48.8	6.46	10.58	44.14	22.12	4.14	1.46	20.98	19.835
CCV_D Threshold (0.0003) Weight (4600)	62.48	10.18	15.46	40.54	23.08	3.32	1.82	34.62	23.9375
CCV_A Threshold (0.0003) Weight (4400)	70.16	2.28	24.78	54.82	22.12	4.8	2.96	30.66	26.5725

Table 6. The processing time for producing the feature vectors of 100 images.

	CCV	CCV_N	CCV with Angle and Distance
The Processing Time in ms	8703	8734	9281

Table 7, shows the cost of retrieving for the first 100 retrieved images.

Table 7. The processing time for retrieving the first 100 images.

	CCV	CCV_C	CCV_D	CCV_A
The Processing Time in ms	31	47	63	63

To solve the efficiency problem we suggest developing an efficient indexing structure for the proposed methods and/or to refine the retrieval result of the color histogram or the CCV by re-ranking the top images using the proposed methods [10].

6. Conclusions

This research proposed methods (CCV_N, CCV_D and CCV_A) that take advantages of the coherence regions numbers and locations information. The coherence regions location and number were represented by using the histogram representation technique which is simple and flexible. The histogram representation provides us with the ability to retrieve images by any type of information either singly or by combining different types of coherence regions information. The experiments were carried out on a collection of 1014 color images of which 100 query images were used as stimuli for retrieving similar images from the image collection. The evaluation of the results of the experiments was done by using E_{avg} and Precision-Recall metrics. The experimental results indicate that the proposed methods yielded better retrieval effectiveness than the CCV method in general.

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APPENDIX A

The description of the fourteen manipulated images which used in the second image set

Manipulated Image Name	Original Image Name	Manipulation Technique Name	Size		Color Model	Resolution
			Width	Height		
242_L8.jpg	242.jpg	Lighting	384	256	RGB	72 dpi
40_Sc170.jpg	40.jpg	Resizing without resample	384	256	RGB	42 dpi
284_crop1.jpg	284.jpg	Cropping	328	180	RGB	72 dpi
46_crop1.jpg	46.jpg	Cropping	183	206	RGB	72 dpi
46_L18.jpg	46.jpg	Lighting	384	256	RGB	72 dpi
46_r90.jpg	46.jpg	Rotation	256	384	RGB	72 dpi
298_rot.jpg	298.jpg	Rotation	413	301	RGB	72 dpi
299_Sc130.jpg	299.jpg	Resizing with resample	499	333	RGB	72 dpi
278_Crop1.jpg	278.jpg	Cropping	267	178	RGB	72 dpi
278_Crop2.jpg	278.jpg	Cropping	246	164	RGB	72 dpi
279_L4.jpg	279.jpg	Lighting	384	256	RGB	72 dpi
7_crop.jpg	7.jpg	Cropping	182	213	RGB	72 dpi
7_crop_rot.jpg	7.jpg	Cropping + Rotation	270	249	RGB	72 dpi
7_L7.jpg	7.jpg	Lighting	384	256	RGB	72 dpi

APPENDIX B

The first image set

Figure B.1 : the images of the first image set

APPENDIX C

The second image set

Figure C.1 : the images of the second image set