Image Retrieval System Based on Combination of Color, Texture and Shape Features

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***Abstract*—In the Content-Based Image Retrieval (CBIR) system, an effectiveness of the visual descriptors, such as color, texture and shape, determines a good retrieval performance. Recently, more than two types of visual descriptors are combined to improve the performance of CBIR. The combination method used to combine different types of visual descriptors also plays an important role to obtain a good performance. However, we are aware that researchers have not paid sufficient attention to the combination methods, so in this paper, we focused on combination of schemes of three types of visual features to obtain higher improvement of the retrieval performance. Firstly, several visual descriptors that belong to three types of visual features (color, texture and shaper) are analyzed individually to select a better descriptor from each category. Second, the several combination methods are analyzed to determine a best combination method. The performance of the proposed scheme is compared with some CBIR systems in which more than two different types of descriptors are combined.**

Keywords-CBIR system; color descriptor; texture descriptor; shape descriptor; combination methd of descriptors

I. INTRODUCTION

Multimedia data is very common in daily activities, because nowadays it is easy and inexpensive to take pictures and videos. Digital images and videos are not only important in common activities, but also in areas such as medicine, biology, astronomy, commerce, tourism, etc. Due to the importance of multimedia information, the facility of sharing these data trough high-speed Internet connections and the high storage capacities, the size of databases has been increasing considerably. As a consequence of this situation, an efficient classification, indexing and retrieval of digital images stored in a huge database have been challengeable tasks. Therefore, the Content-Based Image Retrieval (CBIR) has become an urgent research topic because the traditional retrieval method, that is manual and subjective process, has become time consuming operation with ambiguity results in a huge database.

The CBIR systems describe multimedia content using visual features, such as color, texture, shape, etc. These features are low-level visual features, which describe images making the information retrieval be fast, objective and automatic. In general, color is one of the most dominant and distinguishable features in describing image [1]. Therefore, until now, several color-based descriptors have been proposed in the literature [2]-[6]. The Histogram Intersection (HI) [2], the Color Correlogram (CC) [3], the Dominant Color Descriptor (DCD) [4], the Color Layout Descriptor (CLD) [5] and the Color Structure Descriptor (CSD) [6] are widely used as color-based descriptors in the CBIR. To improve the retrieval performance, Atoany et al. [7] proposed the Dominant Color Correlogram Descriptor (DCCD), which optimizes the CC using only eight dominant colors. Also, some texture-based descriptors have been proposed in the literature to describe the image using the texture patterns [1][8]-[12]. The steerable filters [1], The Edge Histogram Descriptor (EHD) [8], the Texture Browsing Descriptor [9], the co-occurrence matrix-based descriptors [10][11] and Local Binary Pattern (LBP) [12] are some of the most widely used texture-based descriptors. The shape feature is another important factor that can be used to identify objects and classify the image context. As the shape-based descriptors, the Fourier Descriptor (FD) [13], the moment-based descriptors, such as Pseudo-Zernike Moments (PZM) [1] and Polar Harmonic Transforms (PHT) [14], and Pyramidal Histogram of Oriented Gradients (PHOG) [15] have been used in the CBIR systems.

There are some algorithms that do not use the above mentioned visual features to characterize the images and retrieve desired images. The Scale-Invariant Feature Transform (SIFT) and Speed Up Robust Feature (SURF) are examples of these types of algorithm. In the CBIR system, the SIFT and the SURF obtain some robust interest points, and using these points together with their neighborhood regions, the relevant images are retrieved [16][17]. Recently, the learning-based approaches, such as bag-of-visual-word [18] and the deep learning [19] are used to solve the practical problem in the CBIR.

In order to improve the image retrieval performance, it is necessary to combine more than one visual feature. Several combination or fusion methods are proposed in the literature [20]-[23]. The simplest method is concatenation of two or three descriptors to generate one descriptor with large number of elements [20], while in [21], the descriptors related to color, texture and shape features are combined to generate a single completed binary region descriptor

(CBRD); in this case the combination is not simple concatenation. In another combination scheme, different types of descriptors are applied to image database in the cascade or the parallel manner [22][23]. In [22], firstly, color-based descriptor is applied to retrieve a sub-set of relevant images, and then, shape-based descriptor is applied to images belonging to the previously retrieved sub-set only. In the parallel structure of [23], several sub-sets of relevant images are extracted independently using different types of descriptor, and then, the decision stage makes a final set of the relevant images from all extracted sub-sets of images.

In [1][24]-[27], the visual features are lineally combined to improve the retrieval performance, in which the similarity of each feature is independently computed using a distance metric. And then, an adequate weight for each feature is defined to generate a weighted lineal combination of the similarity scores of the different features. This combination scheme provides us a construction of a flexible CBIR scheme depending on the application. For example in the medical image retrieval system, in which the texture feature may be more relevant than other features, the weight value assigned to texture feature can be more important than color and shape features. In [24] and [25], the color feature and the texture feature are combined. In [24], the CLD and the Texture Browsing Descriptor are used, while in [25], the EHD and several color-based descriptors, such as the CLD and the CSD, are used. In [26], the DCCD as color feature and the PHOG as shape feature are combined lineally. In [1] and [27], three features are used. In [1], the DCD, the steerable filter and the PZM are used as color, texture and shape features, respectively. The color histogram and moments as color feature, texture feature based on Gabor filter and the PZM as shape feature are combined lineally in [27].

In this paper, we propose a CBIR system, in which color, texture and shape-based descriptors are obtained and three distances between query image and database image using these three descriptors are calculated. And then, three distances are lineally combined using adequate weights. Firstly, we analyzed individually several visual descriptors, which belong to one of three types of descriptors in order to select the most adequate descriptor from each category. As color descriptor, we select the DCCD, which was proposed by Atoany et al. [7]. As texture-based descriptor, we selected the directional local motif XoR patterns (DLMXoRP) [11] and, finally, the shape feature is extracted using the PHOG descriptor [15]. Next, the weights for three features are adapted, varying their values, to improve the retrieval performance. The proposed scheme was evaluated using some common metrics used in the CBIR systems such as Average Normalized Modified Retrieval Rank (ANMRR), Average Retrieval Rate (ARR) and Average Retrieval Precision (ARP), and it was compared with some CBIR systems which combined two or more visual features.

The rest of this paper is organized as follows: In Section II, we explain the color-based descriptor used in our CBIR system, and its performance is compared with other color descriptors. In Section III, we present the texture-based descriptor used in our CBIR system together with the performance of this descriptor, and in Section IV, the selected shape-based descriptor and its performance are provided. In Section V, we provide an analysis of the combination methods of the selected three types of descriptors and the global performance of the proposed CBIR system. Finally, in Section VI, we conclude this work.

II. COLOR-BASED DESCRIPTOR

Color descriptors are divided into two categories, i) global color descriptors take into account the whole image in order to extract color information, this process does not include pre-processing or image segmentation; ii) local color descriptors extract spatial information on how pixels are distributed in certain region, and this is done using pre-processing or image segmentation [28]. Several color-based descriptors were proposed in literature, and some of them were adopted by the MPEG-7.

In the proposed CBIR system, we selected DCCD [7] due to its better performance and compact representation.

A. Dominant Color Correlogram Descriptor (DCCD)

First, the image is converted from RGB to HSV color space, because this color space presents more similarity to the human color perception. Then, the HSV image is quantized [4], in order to reduce the computational cost. This color quantization is done as:

$$H = \begin{cases} 0 \text{ } if \text{ } h & \in [316,20) \\ 1 \text{ } if \text{ } h & \in [20,40) \\ 2 \text{ } if \text{ } h & \in [40,75) \\ 3 \text{ } if \text{ } h & \in [75,155) \\ 4 \text{ } if \text{ } h & \in [155,190) \\ 5 \text{ } if \text{ } h & \in [190,270) \\ 6 \text{ } if \text{ } h & \in [270,295) \\ 7 \text{ } if \text{ } h & \in [295,316) \end{cases} \quad (1)$$

$$S = \begin{cases} 0, & \text{if } s \in [0,0.2] \\ 1, & \text{if } s \in (0.2,0.7] \\ 2, & \text{if } s \in (0.7,1] \end{cases} \qquad V = \begin{cases} 0, & \text{if } v \in [0,0.2] \\ 1, & \text{if } v \in (0.2,0.7] \\ 2, & \text{if } v \in (0.7,1] \end{cases} \quad (2)$$

We only consider the 8 more representative hues (red, orange, yellow, green, blue, dark blue, purple, violet), and three levels for saturation (S) and value (V). It is important to mention that Human Visual System (HVS) is irregular, that is the reason why we are using this method of color quantification. The dominant colors are determined from the quantized image with 72 colors, which is given by:

$$F = \{\{c_i, P_i\}, i = 1, \dots, M\} \quad (3)$$

where M<72 is the numbers of dominant colors of a quantized image, c_i is *i-th* dominant color with three components (H,S,V) and P_i is the percentage of the dominant color c_i. Firstly, the percentages Q_j, j=0,..., 71, of all existent colors are calculated, and then, M colors c_i,

i=0,…, M-1 with the first M largest percentage are extracted as dominant colors, in this paper, we use M=8 dominant colors. Then, the percentages of each dominant color c_i is adjusted as

$$P_i = \frac{\overline{p_i}}{\sum_{j=0}^{M-1} Q_j} \tag{4}$$

$$i = 0,1, \dots, M-1, \quad j = 0,1, \dots, 71$$

where $\bar{p}_i = Q_i$ if c_i is a dominant color, otherwise $\overline{p_i} = 0$. Once dominant colors are obtained, the correlation of pair pixels of the same dominant color is calculated using color correlogram [3], and it is defines as:

$$\gamma_{c_i c_i}(I) \triangleq Pr_{p_1 \in I_{c_i}, p_2 \in I_{c_i}}[p_2 \in I_{c_i} | |p_1 - p_2| = 1] \tag{5}$$

where $\gamma_{c_i c_i}(I)$, is the probability of finding a pixel p_1 of color c_i away from another pixel p_2 of the same color. Obtaining this correlogram for all dominant color c_i with $i = 0, 1, \dots, M-1$, we get the DCCD, which is given by

$$DCCD = \{c_i, CC_i\} \tag{6}$$

where CC_i is the color correlogram of *i-th* dominant color c_i.

B. *Performace comparison of color-based descriptors*

The performance of the DCCD is compared with other conventional color-based descriptors. Table I shows experimental results of the DCCD together with six color-based descriptors using the *Database 2,* composed by 1000 Corel images, divided into 10 categories with 100 ground truth images per category. From the Table I, the DCCD and the conventional CC descriptors show better performance, although DCCD is 8 times more compact than the CC [3].

TABLE I. COMPARISON RESULTS OF TEXTURE-BASED DESCRIPTORS

Method	ANMRR	ARR α 2	ARR & ARP α 1	ARR α $\frac{1}{2}$	ARP α $\frac{1}{4}$
DCCD	**0.3086**	0.7590	0.**5960**	0.7560	0.8840
CC	0.3228	0.7200	0.5870	**0.7620**	**0.8880**
IH	0.3174	0.7610	0.5760	0.7380	0.8640
DCD	0.3384	0.7420	0.5590	0.6920	0.8480
LBA	0.3478	0.7320	0.5500	0.7040	0.8000
CLD	0.3194	**0.7620**	0.5740	0.7280	0.8360
CSD	0.4431	0.6190	0.4630	0.6200	0.7680

Taking into account the good performance and compactness of the DCCD, we select it as color-based descriptor.

III. TEXTURE-BASED DESCRIPTOR

Texture is an important property for characterization and recognition of image [8][10]. We analyzed the performance of several texture-based descriptors in order to select the most efficient one.

A. *Directional Local Motif Xor Pattern (DLMXoRP)*

The DLMXoRP [11] is one of the high-performance texture-based descriptors, in which an input image is divided into 3x3 overlapping blocks and a vector at a specific direction is extracted as shown by Figure 1.

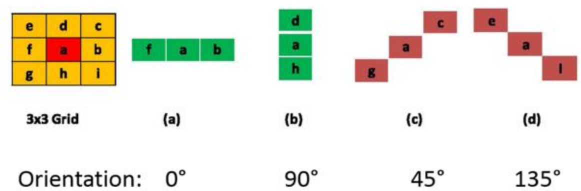


Figure 1. 3-element vector extraction [11]

In Figure 2 we can observe that a number of motif (1,2…,7) is assigned depending on the relation between the three pixel values of the extracted vector as follows [11]:

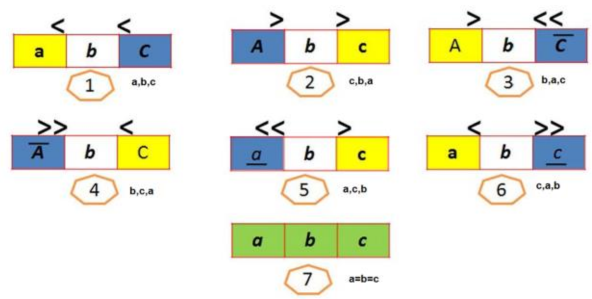


Figure 2. Seven motif asigment [11]

In order to extract the texture features, the following equations are used

$$DLMXoR_{N,R} = \sum_{i=0}^{N-1} T_{im}(p_i, p_c) \times 2^i \tag{7}$$

where:

$$T_{im} = \begin{cases} 1 & p_i \neq p_c \\ 0 & p_i = p_c \end{cases} \tag{8}$$

And N is the number of neighbor pixels, R is the radio of the 3x3 overlapping block, p_c is the central pixel and p_i , i=0,.. 7, are the neighbor pixels. Using this information, a histogram is computed by:

$$H_{DLMXoRp}^{\theta}(l) = \sum_{i=1}^{N_1} \sum_{j=1}^{N_2} f_2(DLMXoRP^{\theta}(i,j), l) \tag{9}$$

$$l \in [0, 2^N - 1]$$

where $\theta = [0°, 45°, 90°, 135°]$ and:

$$f_2(x, y) = \begin{cases} 1 & x = y \\ 0 & x \neq y \end{cases} \tag{10}$$

Finally, the obtained histograms are concatenated as:

$$H_{DLMXoRP} = [H_{DLMXoRP}^{0°}, H_{DLMXoRP}^{45°}, H_{DLMXoRP}^{90°}, H_{DLMXoRP}^{135°}] \tag{11}$$

B. *Performance comparison of texture-based descriptors*

To select the most efficient texture-based descriptor, we carried out a performance comparison of several texture-based descriptors, such as MCM [10] and DLMXoRP [11]. Vipparthi and Kagar [11] compared their DLMXoRP with several LBP-based descriptors, showing superiority of this descriptor. We also compared Steerable Filters [1] and the EHD [8]. In this evaluation, we used some metrics commonly used in image retrieval evaluation, such as ANMMR, ARR and ARP, using the Corel Dataset 1k. The evaluation results of four texture-based descriptors are shown in the Table II.

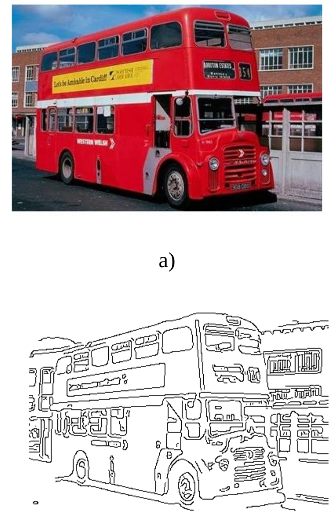
TABLE II. COMPARISON RESULTS OF TEXTURE-BASED DESCRIPTORS

Metric	Steerable Filter	MCM	DLMXoRP	EHD
ANMRR	0.5144	0.5404	**0.4460**	0.5401
ARR $\alpha = 2$	0.5820	0.5410	**0.6140**	0.5550
ARR $\alpha = 1$	0.4010	0.3810	**0.4680**	0.3790
ARP $\alpha = 1$	0.4010	0.3810	**0.4680**	0.3790
ARP $\alpha = 0.5$	0.4620	0.4660	**0.5960**	0.4400
ARP $\alpha = 0.25$	0.5120	0.5560	**0.6720**	0.5000

As shown in the Table II, the DLMXoRP provides a better performance in the CBIR task, therefore we selected this descriptor as the texture-based descriptor in our proposed CBIR system.

IV. SHAPE-BASED DESCRIPTOR

Shape is known to play an important role in human recognition and perception, providing a powerful clue to object identity [1].



a)

b)

Figure 3. Edge information extraction. a) RGB image, b)edge information

Shape-based descriptors can be categorized into two classes [13]: i) contour-based descriptors, which use the boundary information only, ignoring important information in the interior of the objects, ii) region-based descriptors, which use both, boundary and the interior information of objects.

A. *Pyramid Histogram of Oriented Gradients (PHOG)*

In the proposed CBIR system, we selected the PHOG descriptor [15], which extracts boundary information from the object.

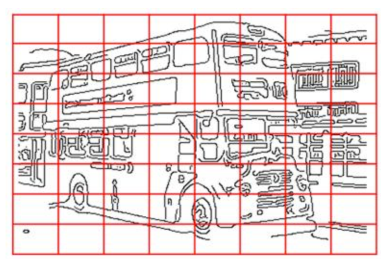


Figure 4. Segmentation of the edge image

This descriptor extracts the edges from a gray-scale image using Canny edge detector, as shown in Figure 3. Then, the image is divided into several blocks (Figure 4) in hierarchical manner to generate several pyramid levels, and in each pyramid level, a histogram of oriented gradients is computed. Finally, the PHOG descriptor is obtained concatenating all these histograms [15].

B. *Performance comparison of shape-based descriptors*

To select the most powerful shape-based descriptor, some conventional shape-based descriptors, such as PZM

[1], two representations of the PHT, which are Polar Complex Exponential Transform (PCET) and Polar Cosine Transform (PCT) [14], and the PHOG, are evaluated. The comparison results are shown by Table III.

TABLE III. COMPARISON RESULTS OF SHAPE-BASED DESCRIPTORS

Metric	PZM	PCET	PCT	PHOG
ANMRR	0.7177	0.7212	0.7066	**0.5825**
ARR $\alpha = 2$	0.3808	0.3642	0.3554	**0.4462**
ARR $\alpha = 1$	0.2000	0.2231	0.2423	**0.3538**
ARP $\alpha = 1$	0.2000	0.2331	0.2423	**0.3538**
ARP $\alpha = 0.5$	0.2308	0.2615	0.2538	**0.4692**
ARP $\alpha = 0.25$	0.3692	0.3692	0.3692	**0.6308**

From the Table III, we can observe that the PHOG outperforms other shape-based descriptors, so we decided to incorporate it as the shape-based descriptor in our CBIR system.

V. EXPERIMENTAL RESULTS

The most adequate three descriptors, which are the DCCD as color-based descriptor, the DLMXoRP as texture-based descriptor and the PHOG as shape-based descriptor, were selected through the performance comparison in the CBIR system, we analyzed several combination methods of these three descriptors. The combination of the three visual descriptors is done using a weighted linear combination given by

$$S(I,Q) = \omega_c S_{color}(I,Q) + \omega_t S_{tex}(I,Q) + \omega_s S_{shape}(I,Q) \qquad (12)$$

where I and Q are an image extracted from database and a given query image, respectively, and $S_{color}(I,Q)$, $S_{tex}(I,Q)$ and $S_{shape}(I,Q)$ are individual scores of image I respect to the query image Q in color, texture and shape aspects, respectively, and $S(I,Q)$ is the global score of I respect to Q. The weight values: ω_c, ω_t and ω_s present the grades of importance of each visual feature, and $\omega_c+\omega_t+\omega_s=1$ must be satisfied.

To determine the most adequate combination of three weight values, the performance of proposed CBIR system is evaluated varying these three values using Corel Dataset 1K, which are shown by Table IV. In Figure 5, we present the image retrieval behavior for each class at a specific weight combination. From Table IV and Figure 5, we can observe that using combination number 7, which presents $\omega_C = 0.2, \omega_T = 0.3, \omega_S = 0.5$, the performance of the image retrieval task is improved.

TABLE IV. CBIR PERFORMANCE WITH DIFFERENT COMBINATIONS OF THREE WEIGHT VALUES

Weights	ANMRR	ARR α 2	ARR & ARP α 1	ARR α $\frac{1}{2}$	ARP α $\frac{1}{4}$
$\omega_C = 0.3$ $\omega_T = 0.3$ $\omega_S = 0.3$	0.3387	0.7520	0.5610	0.6980	0.7880
$\omega_C = 0.5$ $\omega_T = 0.3$ $\omega_S = 0.2$	0.3510	0.7390	0.5470	0.6820	0.7600
$\omega_C = 0.5$ $\omega_T = 0.2$ $\omega_S = 0.3$	0.3584	0.7290	0.5410	0.6700	0.7520
$\omega_C = 0.2$ $\omega_T = 0.5$ $\omega_S = 0.3$	0.3353	0.7360	0.5660	**0.7200**	**0.8200**
$\omega_C = 0.3$ $\omega_T = 0.5$ $\omega_S = 0.2$	0.3346	0.7390	0.5670	0.7040	0.8120
$\omega_C = 0.3$ $\omega_T = 0.2$ $\omega_S = 0.5$	0.3421	0.7550	0.5570	0.6780	0.7800
$\omega_C = 0.2$ $\omega_T = 0.3$ $\omega_S = 0.5$	**0.3306**	**0.7600**	**0.5760**	0.7060	0.8080
$\omega_C = 0.4$ $\omega_T = 0.4$ $\omega_S = 0.2$	0.3413	0.7490	0.5570	0.6960	0.7760
$\omega_C = 0.2$ $\omega_T = 0.4$ $\omega_S = 0.4$	0.3321	0.7410	0.5690	0.7180	0.8160
$\omega_C = 0.4$ $\omega_T = 0.2$ $\omega_S = 0.4$	0.3511	0.7390	0.5490	0.6840	0.7600

The proposed CBIR system with optimum weight values, obtained through above mentioned observation, is evaluated comparing with other CBIR schemes [1][26]. Both CBIR schemes use more than two visual descriptors, in [1], the DCD based on LBA algorithm is used as color-based descriptor, the PZM and Steerable filter are used as shape-based descriptor and texture-based descriptor, respectively. While in [26], the DCCD and the PHOG are used as color-based and shape-based descriptors, respectively. The comparison results are shown by Table V.

TABLE V. PERFORMANCE COMPARISON

Metric	LBA+PZM + Steerable Filters [1]	DCCD +PHOG [26]	Proposed
ANMRR	0.3672	0.2698	**0.1821**
ARR $\alpha = 2$	0.6750	0.7800	**0.8560**
ARR $\alpha = 1$	0.5420	0.6550	**0.7370**
ARP $\alpha = 1$	0.5420	0.6550	**0.7370**
ARP $\alpha = 0.5$	0.7020	0.8120	**0.8940**
ARP $\alpha = 0.25$	0.8400	0.9320	**0.9577**

The comparisons show that the proposed CBIR scheme, which combines color, texture and shape based descriptors with optimum weight values, provides much better performance compared with other CBIR systems previously proposed.

VI. CONCLUSIONS

In this paper, we analyzed several visual descriptors that belong to color-based, texture-based and shape-based descriptors. Through the performance analysis of color-based descriptors in the CBIR task, we determined that the DCCD is the most efficient color-based descriptor from its retrieval performance and compact representation. As texture-based descriptor, we selected the DLMXoRP considering its higher performance compared with the conventional texture-based descriptors, while the PHOG descriptor shows much better performance compared with other shape-based descriptors, such as the PZM and the PHT descriptors, so this descriptor is selected as shape-based descriptor in the proposed CBIR.

The three descriptors are combined lineally, and the weight values are determined after exhaustive evaluations of proposed CBIR system using Corel Dataset 1k. The determined weight values are $\omega_C = 0.2, \omega_T = 0.3, \omega_S = 0.5$, respectively, which means that the shape feature is most important compared with other two features to retrieve desired images respect to a given query image. The comparison results show that the proposed CBIR scheme outperforms considerably other CBIR schemes.

The optimum weight values are varied depending on the given query image, so adaptive process according to a given query image to determine optimum weight values can be used, which is our feature work.

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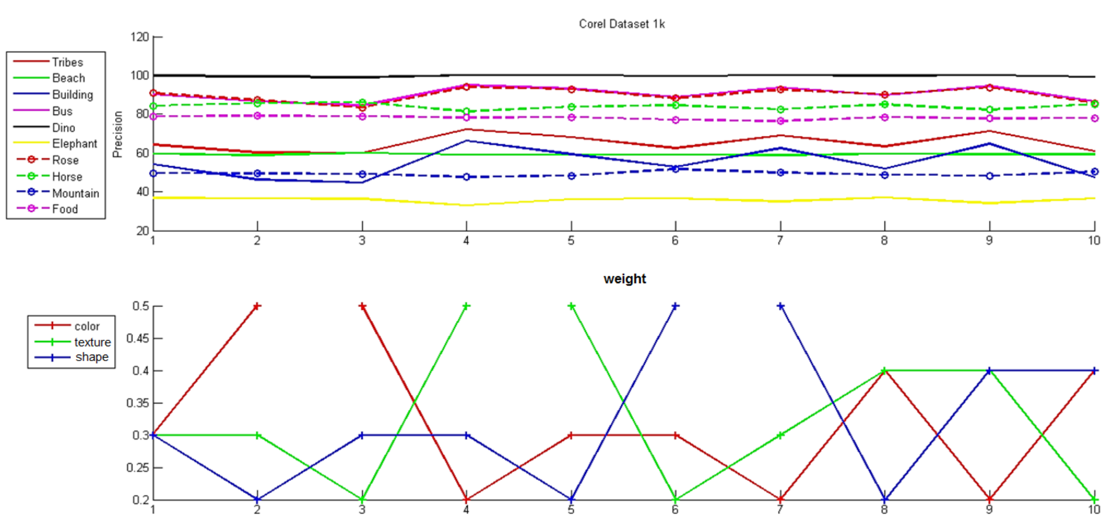

Figure 5. Average precision usgin Corel Dataset 1k

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