ISE: Interactive Image Search using Visual Content

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Abstract: CBIR (Content-Based Image Retrieval) is an image retrieval method that exploits the feature vector of the image as the retrieval index, which is based upon the content, including colors, textures, shapes and distributions of objects in the image, etc. The implementation of the image feature vector and the searching process take a great influence upon the efficiency and result of the CBIR. In this paper, we are introducing a new CBIR system called ISE based on the optimum combination of color and texture descriptors, in order to improve the quality of image recovery using the Particle Swarm Optimization algorithm (PSO). Our system operates also the Interactive Genetic Approach (GA) for a better research output. The performance analysis shows that the suggested 'DC' method upgrades the average precision metric from 66.6% to 89.50% for the Food category color histogram, from 77.7% to 100% concerning CCV for the Flower category, and from 44.4% to 67.65% regarding co-occurrence matrix for the Building category using the Corel data set. Besides, our ISE system showcases an average precision of% 95.43 which is significantly higher than other CBIR systems presented in related works.

1 INTRODUCTION

Nowadays, image-based practical apps have become available everywhere, whether on TV channels, in newspapers, museums and even among. Internet search engines that suggest image search solutions. These images indexing and retrieving depend mainly on text annotations or text elements that can be attributed to them. In many cases (TV channels, newspapers, etc.), the archiving of images and video recording is done only through a manual annotation step using keywords. This indexation represents a long-term and recurring task for humans, especially with the image bases increasingly growing. Moreover, this task depends highly on each person's culture, knowledge and feelings.

In the other hand, with the massive escalation in the number of videos accessible to the public thanks to technical progress, the prices of memory supports have witnessed a dramatic decline over the last decade while their storage capacity has sensibly risen. This availability also gave rise to the creation of several storage possibilities in computing systems to keep up with the development of video files. However, a subsequent growth in exploitation tools is also needed to allow the user to access and handle these documents efficiently. It is within this framework that CBIR systems have proven to be of a high efficiency for researchers as they have been conceived to ensure “an automatic indexing and searching system” which is able to “retrieve an image based on its visual features” (Kundu et al., 2015), (Yue et al.,2011).

Considering this context, a visual content image search system needs to be established. In the literature CBIR several systems are proposed extract the image features with innovative methods (Singha et al., 2012), (Sandid et al., 2015), (Farsi et al 2013). The main limitation of the proposed works is the fact that they don’t consider the user feedback to improve the result of the image retrieval. In fact, this consideration can be made using genetic algorithm. In this paper, a new CBIR method based on genetic algorithm is proposed.

The innovative aspects of the proposed method are as follows:

- Combine usual descriptors features to obtain a new DC descriptor.

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- Optimize the result of DC descriptor by applying the genetic algorithm initially proposed by Holland (Holland., 1975).

The rest of this paper is organized as follows: Section 2 focuses on some important related works. The proposed CBIR system is described in section 3. Experimental setup and results are presented in Section 4, finally, in Section 5, we conclude with the summary of this paper

2 RELATED WORKS

Among the most important recognition aspects are color features. Color in these applications is a solid value because it remains an unchanging parameter that does not alter when the image orientation, size or placement is altered (Dubey et al.,2015). CBIR systems use conventional color features such as dominant color descriptor DCD (Wang et al.,2011), color coherence vector CCV (Pass et al.,1996), color histogram (Singha et al., 2012) and color auto-correlogram (Chun et al., 2008). DCD is about quantifying the space occupied by the color feature of an image by placing its pixels into a measurable number of partitions and calculating the means and ratio of this placement. CCV, however, partitions the image histogram bins into coherent or incoherent types. The results of this method are more precise in that they not only emanate from color histogram classification but also from spatial classification. The accuracy of these results is more palpable when it comes to images that contain rather homogeneous colors (Pass et al.,1996).

Another important recognition aspect is the image texture. Among the most elemental features of an image, we may note the way in which its different regions are arranged. The analysis of texture can provide substantial information about the relationship between the neighbor regions (Sandid et al., 2015), (Rashno et al., 2015). This analysis concerns such common features as those which can be classified into four categories: statistical, structural, model-based and signal processing-based features. These latter have been the most widely used because of their efficiency (Farsi et al 2013). Indeed, among the most used methods of signal processing-based features are Discrete Cosine Transform (DCT), Discrete Sine Transform (DST), Fourier transform Gabor Filter, Wavelet Transform and Curvelet Transform.

The process with which CBIR systems function starts with feature extraction which is an important phase. This extraction is launched with low level features such as color features, which are considered among the primary and most eminent ones. DCD is a pertinent and intuitive color representation as it adopts an effective and concise method to describe the color distribution within an image (Wang et al.,2011). Both color and textural hybrid features were suggested in (Shiv et al.,2015a); these are referred to as rotation and scale-invariant hybrid descriptors (RSHD). The first step in this method is to distribute the RGB color space into 64 partitions so as to quantize the image. Afterwards, the adjacent structural patterns are employed to vehicle the texture information of the image. Another dimension adds up to DCD and the spatial color descriptors which is the semantic feature (Talib et al.,2013). This latter is employed to bridge the gap between the two previously mentioned descriptors. Then, according to the color of each image component and background, the most dominant colors are appointed with different weights.

The system extracts BDIP and BVLC features in (Young et al., 2003) as textural features. In (Yildizer et al.,2012), the system starts with resizing the images into a 128x128 format then applies the wavelet transform to them in 4 levels. The items employed as feature vector are the standard deviation of components in levels 3 and 4 and the LL component. A local wavelet pattern, which is a texture feature descriptor, was proposed in (Shiv et al., 2015b). In order to construct the descriptor, the local wavelet pattern relies on the connection between the local neighbors and the center pixel on the one hand and the circumambient neighbors on the other. In (Shiv et al.,2015c), new local patterns were brought in: the BoF-LBP. This method operates so as, first, to filter the images using the bag of filters (BoF), then to compute the local binary pattern (LBP) over each filtered image and, finally, to concatenate them in order to determine the BoF-LBP descriptor. In (Murala et al., 2012), local tetra patterns (LTrP) were introduced in a way in which the connection between the referenced pixel and its adjacent ones is used so as to allow the computing of texture descriptors.

3 THE PROPOSED CBIR FRAMEWORK “ISE”

Fig.1 shows the overall architecture of the proposed image search system. After preparing the dataset (Corel), The user can introduce a query image. A step of features extraction is applied on the image query (on-line). The used descriptors are explained in detail in section 3.1. The extracted descriptors are after combined to a new descriptor called DC (Descriptor Combination). In the section 3.2 we explain how we combine the extracted features to obtain this new descriptor DC. This process of indexation is applied on the the same images in our database in an offline mode. A step of matching between query vectors and collection vectors is made to obtain the DC vectors. The result is classified according to their degree of relevance with the query vectors.

To improve the result of indexation and search (section 4), we apply the genetic algorithm to the new DC descriptor. Genetic algorithms are the result of the works of Holland (Holland., 1975), (Goldb et al., 1989) in the seventies of the previous century. GAs takes their inspiration from the Darwinian vision of the biological evolution. Indeed, the biological evolution favors individual organisms which are tolerant to variations. The individuals which are the most resistant to the variations of the environmental have more chance to persist and to impose their offspring along the generations. The adaptation of every individual is measured according to a fitness measure representing an objective value taking into account all the constraints of the problem. As defined by Holland, the GA consists of three steps: selection, crossover and mutation.

Later, we will focus on upgrading the results of this method by implementing the genetic algorithm.

The application of the genetic algorithm is as following:

1. Initial population generation phase: Vectors resulting from the DC descriptors.
2. Evaluation and Selection phase: vectors having a distance greater than or equal to 0.6 with respect to the query image descriptor vector using Equation 1 of 3.3.
3. Crossover phase: We can realize this process by cutting two strings at a randomly chosen position and swapping thee two tails. This process, which wee will call one-point crossover in the following, is visualized in Fig.2. We will apply the same principle on descriptor vectors.
4. Mutation phase: Is the occasional introduction of new features in to the solution strings of the population pool to maintain diversity in the population.

Though crossover has the main responsibility to search for the optimal solution , mutation is also

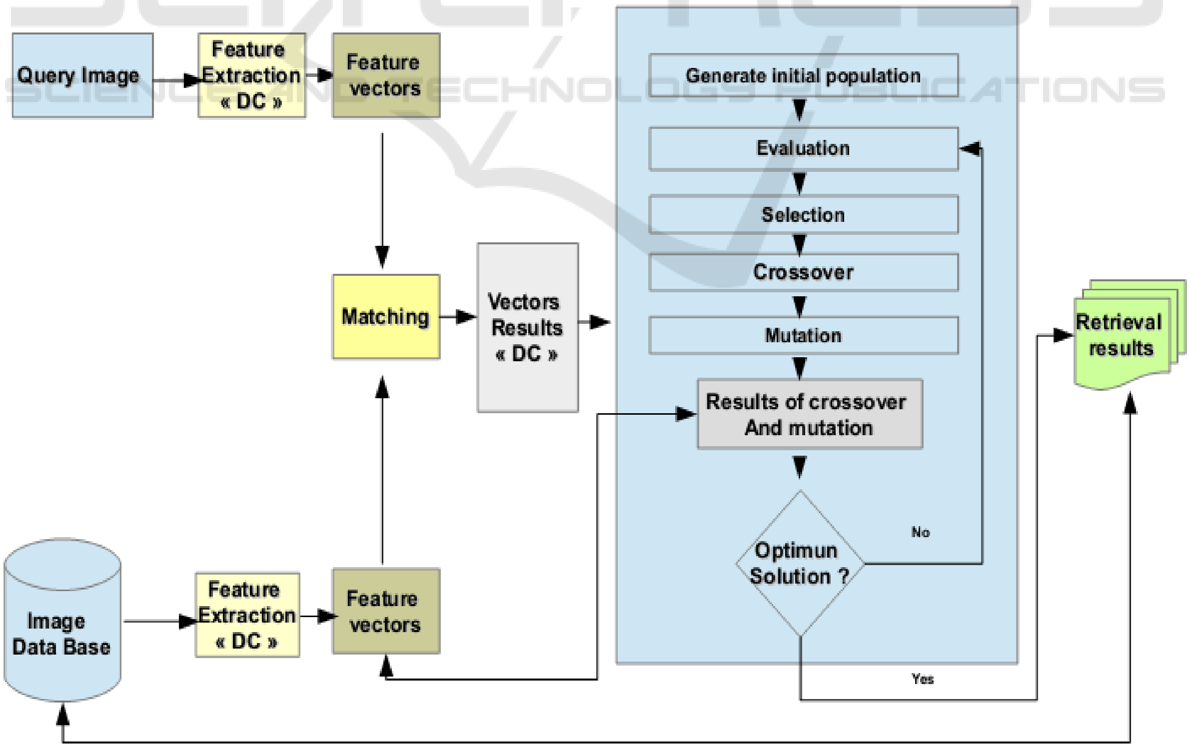

Figure 1: Conceptual Architecture of Search System “ISE”.

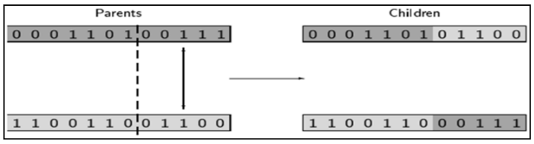

Figure 2: One-point crossover of binary strings.

used for this purpose. We will apply the same principle on descriptor vectors

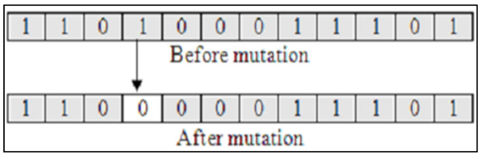

Figure 3: Mutation.

5. Matching: comparing between the cross and mutation resulting vectors and those assigned to describe each image of our base and returning the mot similar vectors. Then, we select the first 20 vectors.
6. Displaying results in the form of images conforming to the 20 selected vectors.
7. Stop Criterion: All result images must have a distance greater than or equal to 0.85 in regards to the query image (otherwise returning to step 2**).**

3.1 Used Descriptors

3.1.1 Color histograms

Color histograms are frequently used to compare images. Examples of their usage in multi-media applications includes scene break detection (Arun et al., 1995), (Kiyotaka et al., 1994) and image database query (Brown et al., 1995), (Myron et al., 1995), (Virginia et al., 1995), (Alex et al.,1996). Their popularity stems from several factors. These factors are listed in the following:

- Color histograms are computationally trivial to compute.
- Small changes in camera viewpoint tend not to effect color histograms.
- Different objects often have distinctive color histograms.

Researchers in computer vision have also investigated color histograms. For example, Swain and Ballard (Michael et al.,1991) describe the use of color histograms for identifying objects. Hafner et al. (James et al., 1995) provide an efficient method for weighted-distance indexing of color histograms. Stricker and Swain (Markus et al., 1994) analyze the information capacity of color histograms, as well as their sensitivity.

3.1.2 Color Coherence Vectors

The color coherence vector CCV represents another more detailed variant of the color histogram. The concept of coherence is linked to a pixel belonging to a considerable size space. Conversely, an incoherent pixel is isolated or belongs to an insignificant size space. The color coherence vector represents this classification of image colors (Greg et al., 1996). The concept of space used hereinbefore refers to a zone of identical color. A labelling technique of connected components enables the generation of regions and adjacency interconnections used of corresponding type 8 (which includes diagonal adjacencies). Pass puts forward precising the threshold beyond which a space is considered coherent at 1% of the image total size (Pass et al., 1996). Ai refers to the number of coherent pixels in the row of color, while βi refers to the number of incoherent pixels. An image CCV is defined by a vector [(α1, β1) (α2, β2) ... (αn, βn)]. The addition of vectors (α1 + β1, α2 + β2... αn + βn) results in the image color histogram.

The key strength of this approach lies in adding spatial information to the histogram through their refinement. This onset delivers more reliable results than those directly derived from histograms analysis. Even with a conventional distance between vectors, this approach consistently delivers good results. Still, it has the drawback of amplifying sensitivity towards light conditions.

3.1.3 Co-occurrence Matrix

The greyscale co-occurrence matrices of an image pixels is the most popular statistical technique (Chen et al.,1979), (Marceau et al.,1990) to extract texture descriptors for various types of images. For instance, the segmentation and classification of images of different types, such as medical images, aerial and astronomical etc. This approach involves exploring the special texture dependencies by constructing a co-occurrence matrix first, based on the orientation and distance between the image pixels. The success of this process depends on parameter proper choice including: the size of the matrix on which the measurement is made, and the distance between the two pixels of the pattern.

3.2 Creation of a New "DC" Descriptor

It goes without saying that a set of features applied to different image types does not necessarily lead to the same results. In other words, a set features which issues a precise retrieval result for a given image type may lead to insufficient results when applied to another category and vice versa.

Table 1: Average precision based on Color histogram, CCV and Co-occurrence matrix for Corel database.

Corel-1K	C_HIST	CCV	Co_Matrix
Africa	88.8	33.3	44.4
Beach	66.6	66.6	22.2
Building	66.6	44.4	44.4
Bus	55.5	33.3	22.2
Dinosaur	100	66.8	88.8
Elephant	33.3	11.1	22.2
Flower	33.3	77.7	33.3
Horse	77.7	55.5	22,2
Mountain	11.1	55.5	55.5
Food	66.6	44.4	66.6
Average	59.9	51	42,1

The previous table may lead us to the conclusion that color histogram provides more efficient results when applied to the themes of “Africa” and “Dinosaur”. On the other hand, better results are obtained from applying CCV on the themes of “Flower” and “Mountain”. The inefficiency of each set of features when applied to certain categories can be restituted by their efficiency or the effectiveness of their combination with other sets of features. The PSO algorithm may be employed in this sense to compensate for such deficiencies.

Introduced by Kennedy and Eberhart, the PSO algorithm has proven to be an adequate solution for different optimization problems (Eberhart et al.,1995). Indeed, PSO operates by modeling the swarm intelligence behavior and finding in the search area the most suitable solution. Each particle in the search area is treated as a potential solution. The observed particle relies on a fitness function to imitate the adjacent particles and stores the optimal solution at the local level (local maxima) and the optimal solution at the global level (global maxima). Furthermore, each particle acts so as to drift to more efficient solutions that best fit its own velocity. This latter is given by the calculation of movements towards local and global maxima.

Color histogram, CVV and coocurrence matrix are the three sets of features that are used in our case. For each of these sets, a corresponding similarity measure is computed. The following diagram shows how the final similarity measure is computed thanks to the incorporation of the three similarity measures explained in Figure 4:

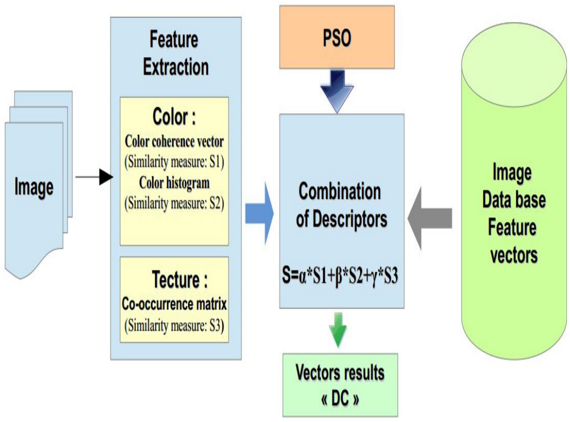

Figure 4: Simplified schema of the DC algorithm.

The three corresponding similarity measures associated with the feature sets Histogram color, CVV and co-ocurrence matrix are respectively assigned the weights α, β and γ. Moreover, the PSO algorithm is applied to 50% of the database (as the training data) to compute the weights. Indeed, the average precision of CBIR corresponds to the fitness function of the PSO algorithm and the particles of this latter are 3D dimension variable (α, β and γ). Hence, while the PSO algorithm aims at finding the variables α, β and γ, it positively affects the average precision of the CBIR system by maximizing it. The Algorithm below represents the PSO (Eberhart et al.,1995) algorithm for feature combination.

Algorithm : PSO.

Let S be the number of particles, x i be the best Known position of particle i and x be the best known position of the entire swarm. The proposed feature algorithm based on PSO is as following:

1. Parameter Initialization:

For each particle i = 1,2, ..., S do:

2. Initialize the weight (***w***), the number of iterations, the maximum velocity (***V max***), the acceleration coefficients ***c 1*** and ***c 2*** and the ranks of the particles For Each dimension.

3. Initialize the particle's position (***x i***) with a uniformly distributed random vector.

4. Initialize the particle's best position Known to its original position: ***xi ← xi.***
5. Calculate the average CBIR precision for all particles and find the swarm's best known position (x).
6. Initialize the particle's velocity: ***v i ~ U (v max, v max).***
7. Until the number of iterations performed or the average CBIR precision value is found, repeat: For each particle ***i = 1,2, ..., S do:***
8. Pick random vectors ***r 1, r 2 ~ U (0,1).***
9. Calculate ***v i (t + 1) = wv i (t) + c 1 r 1 (x i - x i (t)) + c 2 r 2 (x - x i (t))***
10. ***Calculate x i (t + 1) = x i (t) + v i (t + 1)***
11. Calculate the average CBIR precision for ***x i (t + 1)*** and it Refer to ***P (x i (t)).***
12. If P (x i (t + 1))> p (x i) then update the particle's best position Known: ***← x i x i (t + 1).***
13. ***If P (x i (t + 1))> p (x i)*** then update the swarm's best Known position: ***x ← x i (t + 1).***

In the above Algorithm, v I stands for the velocity, w controls the interaction of power between the different particles, while c 1 and c 2 lead the particles into the right directions. In addition, r 1 and r 2 are chosen as random variables that illustrate the idea of stochasticity in the PSO method, x i stands for the position of local maxima and x stands for the position of the overall maxima.

3.3 Similarity Measure

The process returns to measuring the similarity between two images to judge the similarity or dissimilarity. Thus, after representing by vectors the extracted characteristic of the query image and the others images from the database,, We adopt the Euclidean distance to measure the distance between these vectors, in our application, we use the Euclidean distance thanks to its simplicity of calculation of the similarity. This distance is calculated according to the following formula:

$$D(x,y)=\sqrt{\sum_{i=1}^{n}(x_i-y_i)^2} \tag{1}$$

X and y: two images (one query image and the other is an image of the database).
Xi: The query image feature vector,
Yi: The current image feature vector.
Xi-yi: refers to a vector that corresponds to the discrepancy between the vectors xi and yi.

4 EXPERIMENTATION AND RESULTS

The most important evaluating metrics for CBIR performance analysis are precision and recall indexes which are defined as follows:

$$\text{Precision} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of images retrieved}} \tag{2}$$

$$\text{Recall} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of relevant images in the collection}} \tag{3}$$

In experiment, all images of each category are presented as a query image separately, and then the precision of the first 20 retrieved images are computed for each query. Finally, the average precision of all queries are computed and reported for each category.

Table 2: Comparison of the average precision of the previous methods and proposed method.

DB	**Semantic name**	**Average (%)**								
Corel-1K	REF	Sadegh et al., 2017	Chuen et al., 2009	Murala et al., 2012	Yildizer etal., 2012	Kundu et al., 2015	Shiv et al., 2015a	Shiv et al., 2015c	**DC**	**ISE**
	Africa	72.40	68.30	54.95	49.95	73.05	68.95	59.90	**88.05**	**100**
	Beach	51.15	54.00	39.40	71.25	59.35	41.10	50.85	**79.5**	**89.50**
	Building	59.55	56.15	39.60	30.10	61.10	74.30	50.15	**67.65**	**87.10**
	Bus	92.35	88.80	84.30	79.75	69.15	64.40	94.00	**100**	**100**
	Dinosaur	99.90	99.25	94.70	92.05	99.15	99.55	97.60	**100**	**100**
	Elephant	72.70	65.80	36.00	59.45	80.10	56.65	46.65	**93.10**	**100**
	Flower	92.25	89.10	85.85	99.50	80.15	86.55	87.50	**100**	**100**
	Horse	96.60	80.25	57.50	82.25	89.10	93.20	76.50	**100**	**100**
	Mountan	55.75	52.15	29.45	54.60	58.00	55.15	35.25	**77.75**	**77.75**
	Food	72.35	73.25	56.70	20.20	74.50	77.95	56.25	**89.30**	**100**
	Average	76.50	72.70	57.85	63.91	74.36	71.78	65.47	**89.50**	**95.43**

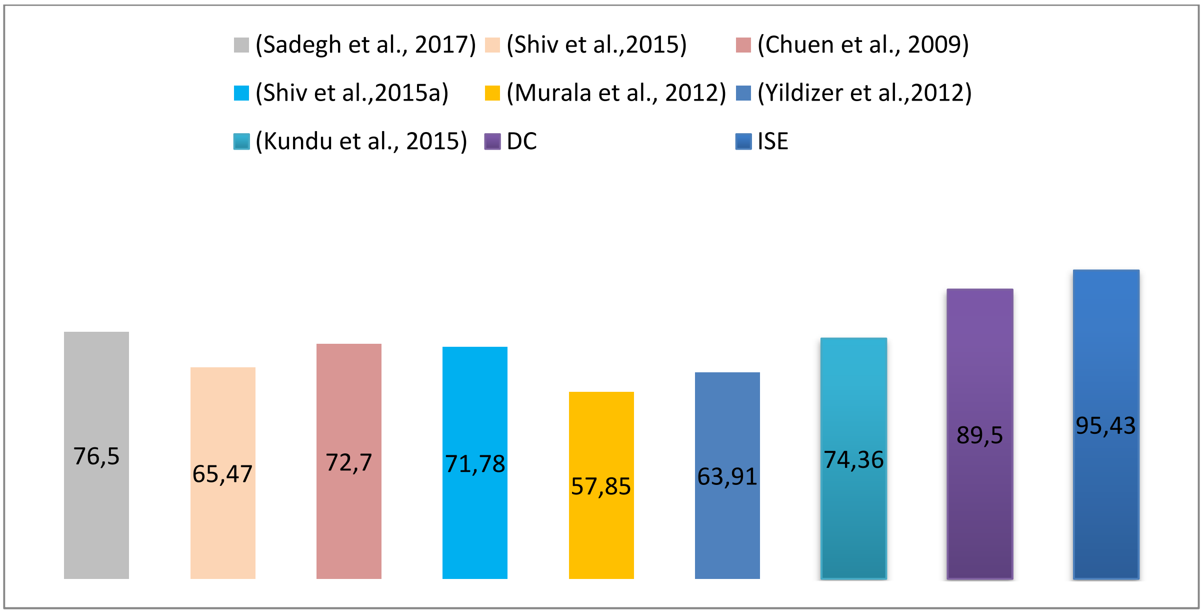

Figure 5: Comparison of the average precision of the previous methods and proposed method.

(a)

(b)

Figure 6: Image retrieval results for Flower a. (Kundu et al., 2015), b. our proposed system ISE.

The overall performance of ISE system with DC feature and Genetic algorithm is compared with some state-of-the-art CBIR systems.

The average precision for all image categories of the Corel-1k dataset is reported in Tab. 2. To show the utility of our CBIR scheme, the results of nine other

CBIR systems are also reported in this table. Since the average precision of our results is %95.43, our CBIR scheme has the highest accuracy among the other state-of-the-art CBIR systems.In fact, our proposed CBIR system outperforms, (Chuen et al., 2009), (Talib et al.,2013), (Yildizer et al.,2012), (Kundu et al., 2015), (Shiv et al.,2015a) and (Shiv et al.,2015c).

The results are depicted in Fig.6. These primary results show that our ISE scheme has better performance results by retrieving20 images correctly among the flower category. On the other hand, the results are17 images for the CBIR of ref (Kundu et al., 2015)

According to the results assessment of an in-depth testing that we have performed, we could actually say that our visual content search system succeeded in demonstrating its reliability and accuracy. These tests enabled us to recognize performance of the new DC descriptor, defined in this article, and of the genetic algorithm for image search. It can be concluded that our ISE system succeeded, to a certain extent, in achieving our target to improve search by visual content.

5 CONCLUSION

In this paper, we have validated our image search system proposal based on the Corel test database. We have developed an image search system called ISE.

ISE allow users to easily access the desired images starting from image query. The innovative features of our new ISE image search system are (i) Defining a new descriptor "DC" and (ii) Applying the genetic algorithm in image search. The application of the genetic algorithm is made to improve results returned by the DC descriptor.

Despite the results that we achieved, the existing visual content image retrieval systems are focusing on addressing particular issues including semantic insufficiency during indexation and retrieval.

However, only a few works are interested in merging visual and semantic contents. Accordingly, developing approaches that focus on this boundary has become necessary. We will therefore tackle this problematic by suggesting a method of image and video documents searching based on a multi-level fusion of visual and semantic.

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