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Powerful Combination of Color Descriptor and LBP Descriptor for Image Retrieval

Nawal Chifa
EEA&TI laboratory, Hassan II University of Casablanca
Faculty of Sciences and Techniques (FSTM)
Mohammedia, Morocco

Abdelmajid Badri
EEA&TI laboratory, Hassan II University of Casablanca
Faculty of Sciences and Techniques (FSTM)
Mohammedia, Morocco

Yassine Ruichek
Syst&Transp Lab, Univ. of Technoogyl. UTBM-90010
Belfort Cedex, France

Aicha Sahel
EEA&TI laboratory, Hassan II University of Casablanca
Faculty of Sciences and Techniques (FSTM)
Mohammedia, Morocco

Khadija Safi
EEA&TI laboratory, Hassan II University of Casablanca
Faculty of Sciences and Techniques (FSTM)
Mohammedia, Morocco

Abstract: The search for visual information in large mass of multimedia data has become essential with the digital evolution. This sparked a need for development of information search techniques by visual content; the performance of such a search system depends largely on the choice of descriptors and technical employees of their extractions. In our work, we present techniques for extracting local and global descriptors applied to two bases of different images, with a connection between the global and local descriptors approach, performed on the two bases of images, followed by a comparative study of different methods used.

Keywords: CBIR, combinations of descriptors, global and local descriptor, Histogram HSV color, LBP descriptor.

1. INTRODUCTION

The development of an image by visual content search system to be effective for large collections of images requires expertise in both image analysis and database management. Such a system is used to characterize images by visual descriptors and search for these images by similarity from these descriptors. Figure1 illustrates this mechanism.

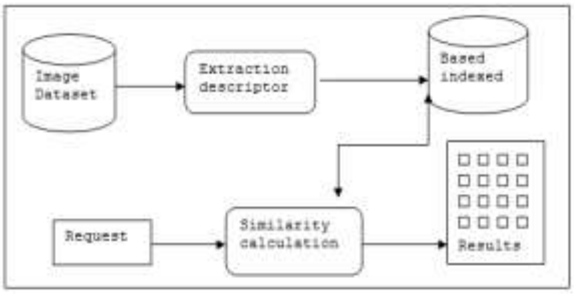


Fig1: Architecture of an image search system.

Image search systems usually deal with extracting visual features, often the color, shape and texture; we use these features in order to provide a comprehensive description of the images [1]. However, these fail when one we want to consider the semantics of the objects described in the image [1] [2].

To overcome this problem, in the following work, we will focus on the extraction of global descriptors images, precisely the color HSV and a local descriptor (operator of local binary patterns) while exploring different methods of connections between them and by conducting a comparative study of these methods on the results.

2. TECHNIQUES AND METHODS USED

Several extraction methods of visual descriptors have been proposed for visual recognition. These image description methods often depend on the applications used. Some distinguishes descriptors reflecting the overall visual appearance of an image, such as color histogram [3], color moments [4], the co-occurrence matrix [5], edge histogram [6], and so on. These features are extracted from the whole of an image and don't give information for the specific region of image. In These global features, unlike in the comprehensive local approaches, methods of local description are intended to describe the content of the image locally. They thus offer the ability to perform a search to on a part of the image or on an object present in the image. The idea of local image descriptors is to extract features from local image region center , This approach involves cutting or segmenting the image into regions of interest , or to determine the points of interest, such as SIFT[7], PCA-SIFT[8],SURF [9],the local binary pattern (LBP) operator[10].

2.1 The data bases used:

In our study, we used two image databases; the first one is a gathering of nature scenes classified according to several themes: The Simplicity dataset is a subset of COREL image dataset. It contains a total of 1000 images, which are equally divided into 10 different categories (Figure2), and the second database contains 810 texture images from nine materials KTH-TIPS-b dataset (Figure 3):

Fig2: The Simplicity dataset is a subset of COREL

Fig3: KTH-TIPS-b dataset

2.2 HSV color histogram:

In our system, the database images are color images. Algorithms calculate histograms colors are easy to implement with a very short turnaround time, introducing invariance to rotation and translation. However, these histograms have no spatial information on the colors of the positions [11]. To overcome this problem we used an image division method for extracting aggregate information partially and collect them later in the same order e(left to right ant top to down) figure4.

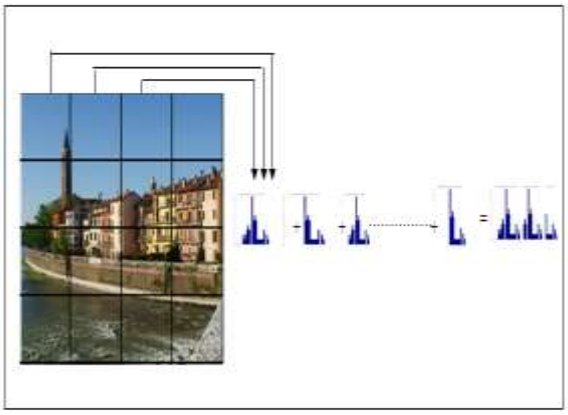


Fig4: Division image to block and extract HSV histogram from each block, and concatenate all of them.

Since the color histogram is sensitive to small changes in brightness, which is problematic if we want to compare similar images, acquired under different conditions, we opted for the HSV color space and we have merged (merged what!!!!) with a descriptor local texture [12], as will be described in the following paragraphs.

2.3 Histogram local binary patterns:

The operator of the local binary patterns (LBP) was proposed in the late 90s by Ojala [13]. Extraction of LBP features is efficient and with the use of multi-scale filters; invariance to scaling and rotation can be achieve. The idea of this texture operator is to assign to each pixel a dependent code grayscale. The gray level of the center pixel (i_c) of coordinates (x_c, y_c) is compared with its neighbors (i_n) using the following equation (1). Figure 5 give an example:

$$\left.\begin{aligned} &\text{LBP}(x_c, y_c) = \textstyle\sum_{n=0}^{p} s(i_n - i_c) \\ &s(i_n - i_c) \quad = 1 \text{ si } i_n - i_c \geq 0 \\ &\qquad\qquad\quad = 0 \text{ si } i_n - i_c < 0 \end{aligned}\right\} \quad (1)$$

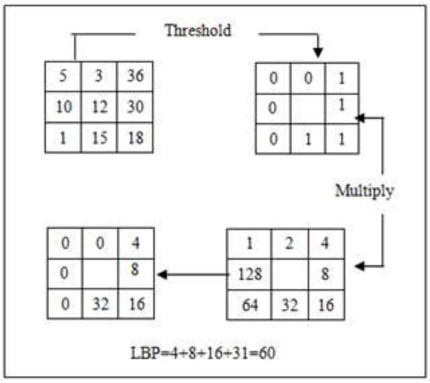


Fig.5

Example for calculation the LBP operator

Where p is the number of neighboring pixels. In general, we consider a neighborhood of 3 * 3 where p = 8 neighbors. So we get, as an image to grayscale, a matrix containing LBP values between 0 and 255 for each pixel. A histogram is calculated based on these values to form the LBP descriptor.

For our descriptor, we used the uniform LBP, which extracts the most fundamental structure from the LBP. A LBP descriptor is considered to be uniform if it has **at most** two *0-1* or *1-0* transitions. For example, the pattern 00001000 (2 transitions) and 10000000 (1 transition) are both considered to be **uniform patterns** since they contain at most two *0-1* and *1-0* transitions. The pattern 01010010 on the other hand is *not* considered a uniform pattern since it has six *0-1* or *1-0* transitions.

Based on this, we propose using those nine uniform patterns that have a U value of at most 2 (00000000, 00000001, 00000011, 00000111, 00001111, 00011111, 00111111, 01111111, and 11111111). These nine patterns correspond to 58 of the 256 original unrotated patterns that can occur in the

3x3 neighborhood. Remaining patterns are accumulated into a single bin, resulting in a 59-bin histogram.

Using only 58/256 of the pattern information may appear as a waste of information, but this approximation is supported by a very important observation. Namely, the chosen nine uniform patterns seem to contribute most of the spatial patterns present in deterministic micro-textures.

In order to obtain the color information with the uniform color LBP features, we calculate the uniform LBP descriptor independently over all the channels (H, S, V), and then concatenating them to get the color LBP, as like in figure 6.

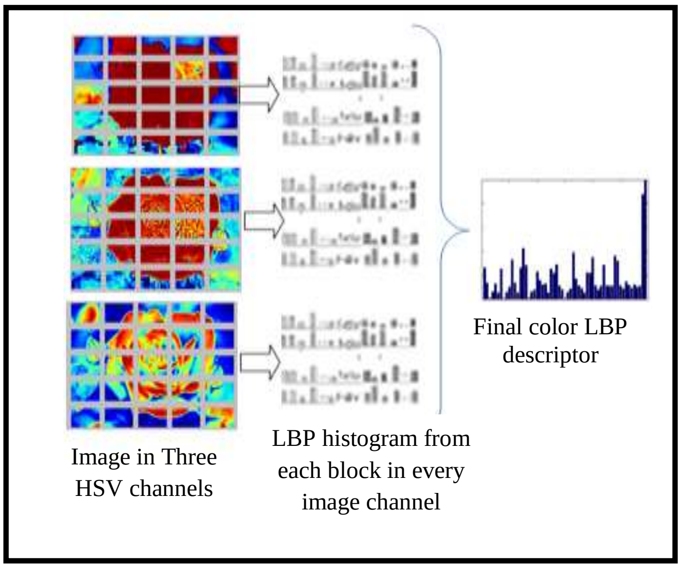


Fig6. Construction of local image descriptor with uniform LBP in three channels HSV

2.4 Combination of descriptors

First we tested and evaluated the results of each method, and this on both image databases, and then to overcome the limitations imposed by each descriptor, we combined the two methods by concatenating the vectors of descriptors and standardizing. And for the calculation of similarity between vectors we opted for the Euclidean distance which proved very optimal for comparing vectors and histograms [14].

- **Step1** : we divide the image to 16blocks for extract descriptor from each block:

- **Step2** : from each block we extract the histogram color and convert the same block to gray for extracting the histogram LBP and concatenate the two vectors

$$V_1 = Vlbp_1 + Vhsv_1$$

- **Step3**: loop over each block, left to right and the top to do down, and concatenate all the vectors in the same order to obtain the vector descriptor :

$$V_2 = Vlbp_2 + Vhsv_2$$
$$V_3 = Vlbp_3 + Vhsv_3$$

.
.
.

$$V_{16} = Vlbp_{16} + Vhsv_{16}$$

Combined descriptor= $\{V1, V_2, V_3 ... V_{16}\}$

3. Experimental results:

To evaluate our methods described above, we have set up an image search system that extracts the visual signatures of each image of the database as a vector of digital values and stores it in a data file. The signature of the query image will be compared later to those stored in the file according to the Euclidean distance, and return images with zero minimum distance to see the query image. To measure the quality of image search system content, parameters precision and recall are conventionally used [15]. Let Ai represents all relevant image results for a given query and Bi represents all the images result returned by the system. We define:

The precision as the ratio between the number of relevant images retrieved and number of images found:

$$Pi = (Ai \cap Bi) / (Bi)$$

The recall as the number of relevant images found on the number of images relevant:

$$Ri = (Ai \cap Bi) / (Ai)$$

Our system is designed to return 25 picture following a query image; for each query we calculate the average retrieval precision (ARP):

$$ARP = \frac{1}{N} \sum_{i=1}^{N} Pi$$

Where N is the size of testing category in dataset.

Table1 Comparison of the ARP values obtained by the proposed method with the standard Corel dataset Image

Descriptors	Block based colorLBP	Block based Histogram HSV	Block based HSV+LBP
Africa	0,7	0,72	**0,94**
Beach	0,3	0,5	**0,58**
Building	0,52	0,42	**0,61**
Bus	0,78	0,48	**0,96**
Dinosaur	1	0,98	**1**
Elephant	0,4	0,52	**0,61**
Flower	0,52	0,72	**0,78**
Horse	0,68	0,96	**0,98**
Mountain	0,54	0,38	**0,58**
Food	0,48	0,68	**0,78**
Average :	***59,2%***	***63,6%***	***78,2%***

Table 1 shows the precision rate for each method , we observe better performance for the combined descriptor on both databases (78%), however the individual use of LBP descriptor gives only (59,2%) and block HSV(63,6%).

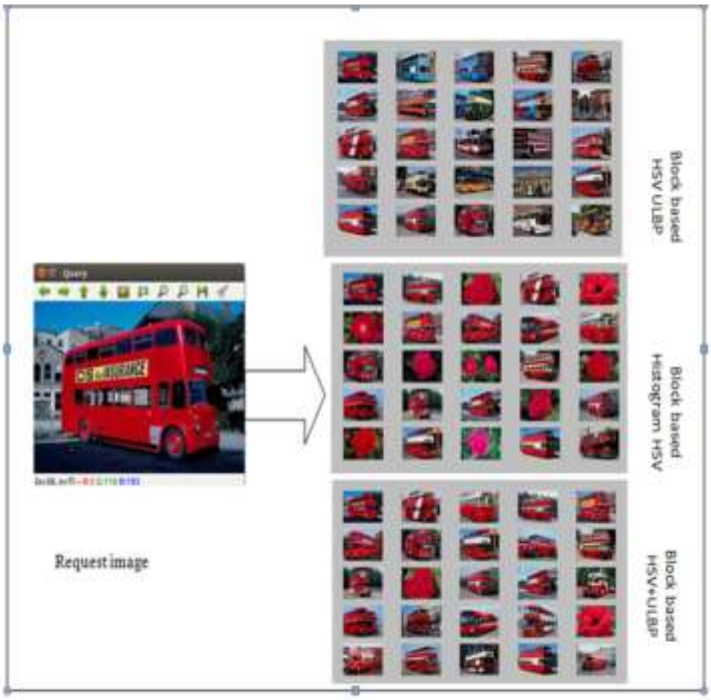
Figure7 illustrates an example query image that found similar results for every method.

The same method was applied on the basis of the texture again. Our combination method has shown very effective results with an important average value (94%) compared to (60% and 77%) for the others methods extracting, as shown in table 2.

Table2: Comparison of the ARP values obtained by the proposed method with the texture dataset

Descriptors / Materials	Block based colorLBP	Block based Histogram HSV	Block based HSV+ULBP
Sandpaper	0,76	0 ,96	1
Aluminum	1	1	1
Styrofoam	0,42	0,9	0,98
Sponge	0,44	0,32	0 ,56
Corduroy	0,42	0,72	0 ,8
Linen	0,68	0,92	0,96
Brown bread	0,63	0,41	0,74
Cracker	0,45	0,9	0,92
Orange peel	0 ,72	1	1
AVERAGE	***60%***	***77%***	***94%***

An example for image retrieval using the three methods extraction is shown in figure7, we can see that the result using the LBP block does not respect the color distribution and the descriptor of color histogram does not respects shape of objects, against the combination of these two descriptors



gives satisfactory result in form and color

Fig7: Example of image result using the three methods

4. CONCLUSION AND PERSPECTIVES:

The histogram LBP and histogram color have no spatial information but in our algorithm we overcome this problem by using an image division method for extracting aggregate information partially and locally, furthermore a merger of descriptors carried out in our research system has shown a visible improvement rate in statistical data.

The effectiveness of a descriptor depends largely on the type of data and their heterogeneity, and the proposed combination in this work proved to be quite satisfactory and can give more performance on other types of base image.so it can be tested on other types of image-based to evaluate the performance of its results and bring him it further improvement by combining different kinds of descriptor and integrating indexing methods in our system.

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